Fall 2018

Enhancing Sidewalk Connectivity within the DART Public Transportation System

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Enhancing Sidewalk Connectivity within the DART Public Transportation System

by

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A professional report submitted to the graduate

faculty in partial fulfillment of the requirements for the degree of

MASTER OF COMMUNITY AND REGIONAL PLANNING

Major: Community and Regional Planning

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2018

DEDICATION

This report is dedicated to my wife Daniela, and my children, Max, Catherina and the new baby. Thanks to their love and support.

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EXECUTIVE SUMMARY

The goal of this study is to identify places where there are gaps in the sidewalk network of eight Des Moines neighborhoods, which if addressed, would enhance connectivity of the sidewalk network. The study is done on behalf of the Des Moines Area Regional Transit (DART) service and focuses especially on how sidewalk connectivity can be enhanced for the riders of the DART bus service. A well-connected sidewalk network helps pedestrians to safely reach their desired bus stop, and sidewalk connectivity has been identified by DART as being a factor in improving the bus riding experience for their patrons.

The eight neighborhoods selected for this study are older, primarily residential neighborhoods to the north and east of downtown Des Moines. The neighborhoods are Cheatom Park, Capitol East, Capitol Park, King-Irving, Martin Luther King, Jr. Park, Mondamin-Presidential, River Bend, and Union Park. These neighborhoods have been identified in previous research as being more disadvantaged areas. These neighborhoods also have more bus stops and routes running through them, and a population that is more likely to be reliant upon public transportation.

To understand how to best enhance connectivity in the sidewalk network, determining the location of missing sidewalks first had to be identified: Identifying Missing Sidewalks. Missing sidewalks were located through the analysis of aerial photography obtained from Polk County in 2017 and involved the use of the geoprocessing tools available within ArcGIS. Three models were developed, to be run sequentially, in order to find missing sidewalk locations. Once the location of missing sidewalks was determined, a framework that would prioritize these missing sidewalks, in a manner which most enhances social justice, was created.

Establishing how to prioritize missing sidewalks involved a multi-step process, which considered socio-economic variables. This step involved Exploratory Spatial Data Analysis. At the block group level, the variables looked at were percentage in Poverty plus Near Poverty, percentage Non-White, and percentage of people holding Graduate or Professional Degrees. Using Exploratory Spatial Data Analysis, these three variables were compared to determine the

areas of need. Areas of need are defined as block groups that a high percentage of Poverty, a high percentage of Non-White and a low percentage of graduate degree attainment. Areas of need were used to prioritize missing sidewalks.

To create the prioritization list of missing sidewalks, Automation was used. A Python script was created that automatically scores missing sidewalks from these data, creating a ranking of highest need for installation of sidewalks to the lowest need. This step also considered spatial distance from bus stops and bus shelters in the analysis of missing sidewalks. Using the walkable distance of a quarter mile, missing sidewalks within this distance were given a higher priority. As conditions change in the future, this script can be re-run and missing sidewalks can be updated.

The results of the study were then validated by comparing the resulting feature class to open source imagery and photos. Once that was completed, the results showed the greatest need for missing sidewalks occurred in two neighborhoods: Capitol East and King-Irving. Capitol East lies directly east of the state Capitol building and is an older working-class neighborhood. King-Irving lies just to the east of Drake. Both of these neighborhoods have diverse populations, with a high level of poverty and a low level of educational attainment. Both neighborhoods lie along bus routes and contain numerous bus stops within their boundaries. When looking at the percentage of missing sidewalks within each neighborhood, Capitol East is missing 19.8% of its sidewalk network, while King-Irving comes in the lowest out of the study area at 6.4%. It is recommended that the priority for sidewalk improvement be focused in the Capitol East neighborhood.

The results found in this study help DART planners to set priorities for sidewalk connectivity improvements and provides a framework for future studies. This study served as a pilot study to identify areas of low sidewalk connectivity. The methodology described in this project, along with the models and script developed for the analysis, can be used by DART to survey their entire of service area. These methods can also be used by other planners throughout North America to improve access to bus service within their communities.

1. INTRODUCTION

Cities throughout the world are investing in public transportation to promote sustainability (Wright & Fulton, 2005). Current auto-centric transportation in cites is not sustainable and is leading to an increase in greenhouse gas emissions, which fuel climate change (EPA, 2017). Within the United States, 27% of greenhouse gas emissions come from burning fossil fuels for transportation (EPA, 2017). Cities that have invested the most into well-connected public transportation systems have the lowest per capita contributions to climate change and are leading the way in mitigating its effects (Dodman, 2009). Planning professionals have looked towards public transportation as one way to support the goal of sustainability.

Part of shifting to a more sustainable development pattern is also related to the promotion of social justice. According to a United Nation's definition, "Social justice may be broadly understood as the fair and compassionate distribution of the fruits of economic growth..." (United Nations, 2006, p. 7). As described by Barret (2001) planners have an important role to play in promoting social justice: planners “have an obligation to expand choices and opportunities for all, not just those who complain” (Barret, 2001, p. 30). Planning and advocating for public transportation can help to increase access to employment and educational opportunities among all people with limited mobility. Investment in public transportation provides people, especially those with low-incomes, with the ability to get to work, access education, and meet their daily needs (Glaser, Kahn, & Rappaport, 2008). To achieve a public transportation system that efficiently serves all people, the built environment around the bus stops must be walkable, since according to a 2016 survey, two-thirds of Americans who take public transportation arrive at their transit stop or station by walking (APTA, 2017).

Throughout the Midwest, major metropolitan areas are investing in walkability and public transportation (Smith, 2010). Central Iowa is no exception and Des Moines Area Regional Transit (DART), the local transit authority, is at the forefront of promoting public transportation. DART identified that part of promoting public transportation involves investments in the built environment around its bus stops. A well-connected sidewalk network serves as a key component of that built environment. DART has identified the connectivity of the sidewalk network within its service area important to pedestrian access at bus stops (TMD, Inc., 2016). This professional report was undertaken with DART as the client. DART expressed interest in understanding the connectivity of sidewalks near their bus stops.[1] Having better pedestrian access has been identified within DART's long-range planning document as providing their customers with a better transit experience (TMD, Inc., 2016).

Within this context, the main goal of this professional report is to spatially analyze the sidewalk connectivity within a subsection of the DART service area. The results of my spatial analysis provided DART with the current condition of their sidewalk connectivity for the first time. This report provided a framework for planners to assess priorities for the installation or repair of sidewalks to support enhanced connectivity. In this professional report, I defined priority missing sidewalks as falling within areas of need. These areas of need were characterized by high percentage of poverty, high percentage of non-White, and a low percentage of Graduate degrees. The prioritization of missing sidewalks additionally looked at two spatial criteria: distance from bus stops and distance from bus shelter. These spatial criteria made the study more applicable to DART. My methodological approach also provides a methodology for DART to conduct future studies of their entire service area. This study also assists the City of Des Moines, and other cities in the metropolitan area, by providing a methodology for detecting missing sidewalks and a script that can be used to prioritize those sidewalks. Written in the Python language, the script is easily adaptable to other variables that municipalities may be of interest in adding to their prioritization criteria for missing sidewalks. Finally, the study also serves as a model for planners working throughout North America that wish to examine sidewalk connectivity around bus stops in their communities.

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[1] In the fall of 2016, Professor Mônica Haddad, my major professor, put me in contact with Ethan Standard, a transportation planner, who worked with DART. Ethan spoke to me about the need within DART to determine the connectivity of the sidewalk network in support of *Forward 2035*. Since meeting with Ethan, he has moved on to pursue different employment. Carl Saxon took over his role and serves as the point of contact at DART for this project. These meetings have led to this project, which proposes a method for a spatial assessment of connectivity in the sidewalk network in DART service area, identifying potential gaps that need to be addressed by local municipalities and regional transit planners to promote connectivity (C. Saxon, personal communication, 2017).

Achieving the goal of this study required the integration of a wide range of socio-economic variables and spatial data derived from a variety of sources. The software ArcMap was used to determine location of the missing sidewalks and develop the models for identifying missing sidewalks. The software GeoDa was used to identify trends in the socio-economic data to determine the areas that had the greatest need for connectivity. Finally, the programming language, Python, was used to write a script that prioritized missing sidewalks, based upon socio-economic variables and distance from bus stops. The intent of this study was to use data, software and methods widely available to planners, so that the results can be replicated by any planner wishing to improve sidewalk connectivity in their community.

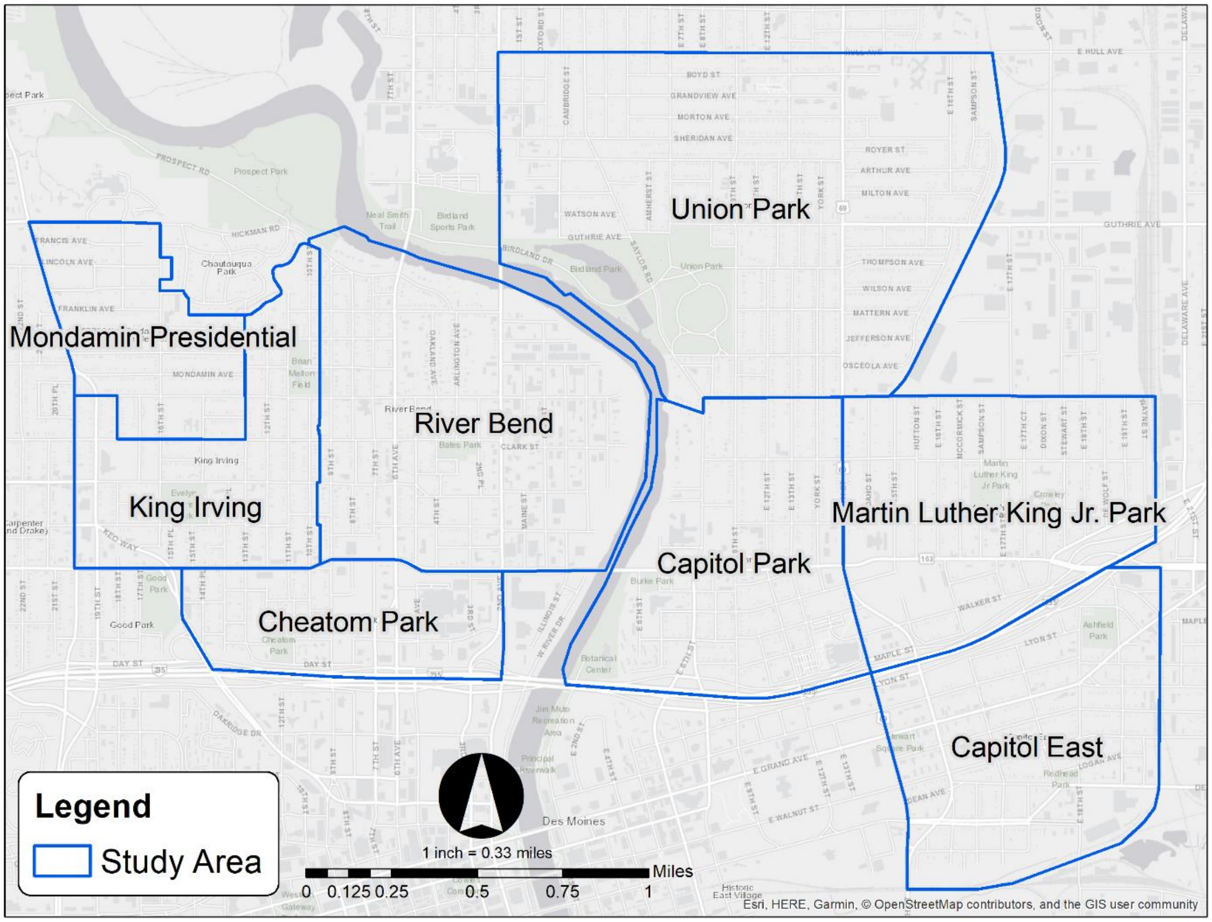
In the remainder of this professional report, I will introduce the study area, which will delimit this case study and introduce information about the Des Moines and the metropolitan region, DART, and planning efforts within the region. I will then present the literature review, which will cover sustainability, planning for social justice and empirical studies. Taking information from the literature review, I will then present the methodology that was developed to conduct this study, with a detailing of the specific steps to be followed. I will then discuss the results and limitations of the study. Finally, I will present recommendations for DART, and suggest future research that could be conducted on sidewalk connectivity.

2. STUDY AREA

The study area was composed of eight neighborhoods within the City of Des Moines. These neighborhoods are north of downtown Des Moines, located on both sides of the Des Moines River. They include, going from west to east: Mondamin Presidential, King Irving, Cheatom Park, River Bend, Union Park, Capitol Park, Martin Luther King, Jr. Park, and Capitol East. Based upon previous research conducted for the neighborhoods' plans, these areas were anticipated to have higher levels of poverty, lower educational attainment, and a greater share of Non-White population. Additionally, the selected study area had seven bus routes that provide service, as well as 131 bus stops. These neighborhoods are largely residential in character and constitute some of the earliest "suburbs" of Des Moines. They have some neighborhood oriented commercial districts, as well as cultural and educational institutions. A significant industrial area is in the River Bend Neighborhood between 2nd Avenue and the Des Moines River and due east of Union Park. The study area selected here, is representative of historic residential areas within Des Moines, and is similar in character to residential areas in other Midwestern cities. This made the study area a good place to develop and test a methodology for increasing sidewalk connectivity.

Initially this project was proposed to analyze the entire MPO served by DART, however the amount of processing time that area would require was beyond the scope of this project. Rather than examine the entire MPO, I decided to select neighborhoods that were more likely to have a higher level of need. The neighborhoods can be considered part of a pilot study, so that others can expand upon the methodology in the future to cover the whole metropolitan area. In the following section these eight neighborhoods were put into the regional and city context.

Figure 1: Study Area



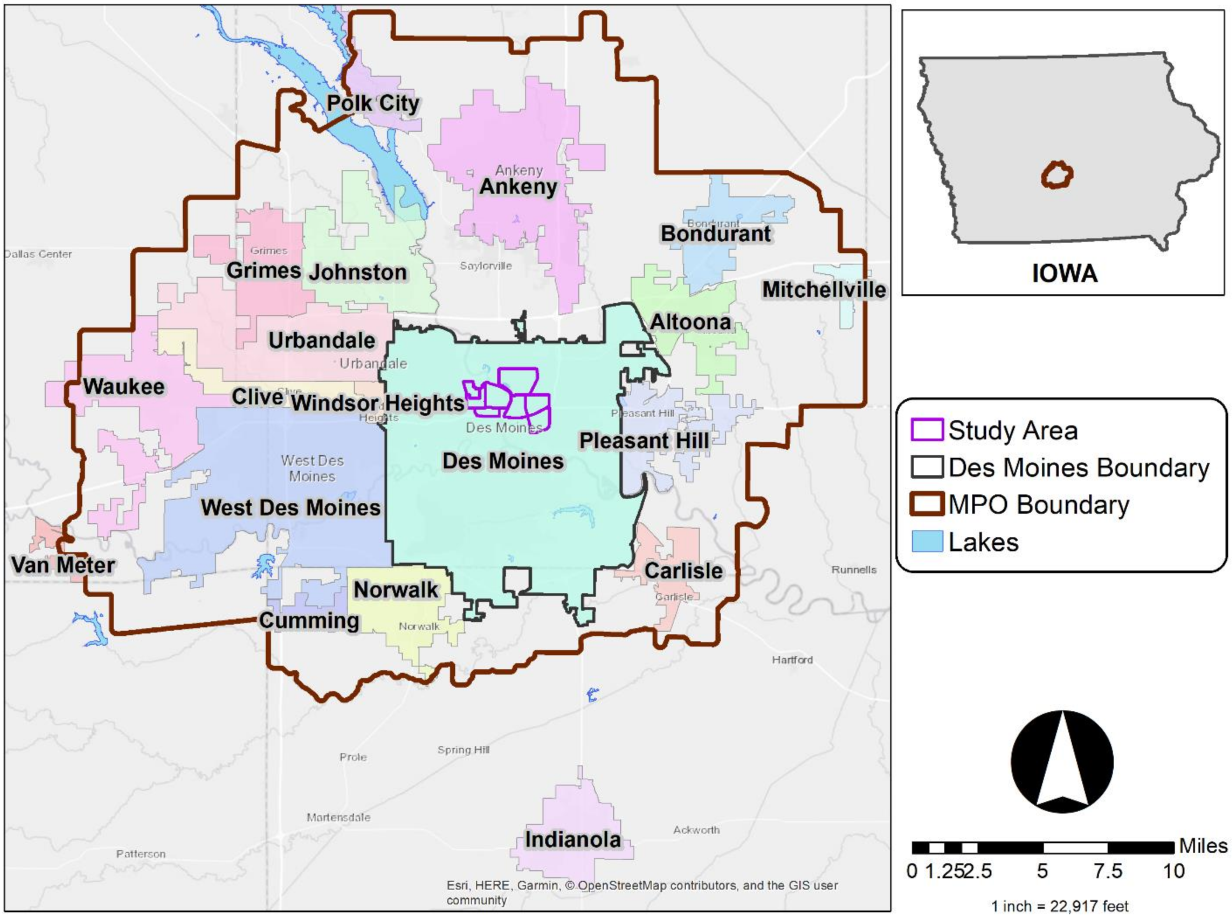
The context for this study was in central Iowa, where the DART service area is located. The Des Moines Area Metropolitan Planning Organization (MPO) serves as the transportation policy-making organization for the metropolitan area. An MPO is a regional body, required by federal law, whose purpose is to create cooperation within regions for transportation projects. The Des Moines Area MPO is composed of 16 local city governments[2], three county governments (Polk, Dallas, and Warren) and DART, as voting members. Non-voting associate members include three cities (Cumming, Indianola, Van Meter) and one county (Madison). Finally, there are five advisory members, the Des Moines International Airport, the Federal Highway Administration,

[2] Altoona, Ankeny, Bondurant, Carlisle, Clive, Des Moines, Grimes, Johnston, Mitchellville, Norwalk, Pleasant Hill, Polk City, Urbandale, Waukee, West Des Moines, and Windsor Heights.

the Federal Transit Administration, the Iowa Department of Transportation, and the Heart of Iowa Regional Transit Agency (Des Moines Area MPO, 2018). The Des Moines MPO is integral in the coordination of inter-jurisdictional plan and projects in central Iowa. In planning its service area, DART utilizes the Des Moines Area Metropolitan Planning Organization (MPO) boundary (TMD, Inc., 2011).

Central Iowa contains the Des Moines metropolitan area, which consists of 18 cities within a three county (Polk, Dallas, and Warren) area. As of 2016, the Des Moines metropolitan area is the largest urbanized area in the state of Iowa, and the 89th largest metropolitan area by population in the United States (U.S. Census Bureau, 2016). The largest and primary city of the metropolitan area is Des Moines. The MPO boundary encompasses around 500 square miles (1,295 square kilometers). This same boundary has been used in other long-range regional plans in central Iowa: The *Tomorrow Plan* (2013) and the *Mobilizing Tomorrow* Plan (2014). The MPO boundary is beyond the scope of this report. However, the methods described in this report to identify sidewalk connectivity in Des Moines can be later applied to the MPO as a whole. A subsection of the City of Des Moines serves as the study area for this case study (Figure 1). Information about the metropolitan area is also included in this section, in order to place the study area within its context.

Figure 2: Des Moines within the MPO Boundary, 2016



The population of the Des Moines Metropolitan Area has increased steadily since the 2010 census, with an annual percentage increase of just fewer than 2% (Table 1), making it the fastest growing region in the Midwest (Aschbrenner, 2017). Des Moines itself has increased its population from 203,433 in 2010, to 216,533 in 2017 (U.S. Census Bureau, 2016), reaching its largest ever population size and reversing the declines that occurred with post-WWII suburbanization. Within the metropolitan area, increasing population has been identified as leading to more congestion on roadways and a need to increase investment in other forms of transportation (DSM MPO, 2013; DSM MPO, 2014; DSM Community Development, 2018). In the city of Des Moines vehicle congestion is especially pertinent, as Des Moines contains the Central Business District and many people commute into the city daily for work and for recreational and cultural amenities.

Table 1: Population Growth in the Des Moines Metropolitan Area, 2010-2016

Year	*Population*	*Percent Change*
2010	552,889	1.7*
2011	562,406	1.7
2012	571,592	1.6
2013	580,913	1.6
2014	590,741	1.7
2015	601,187	1.8
2016	611,755	1.8

* Percent Change in 2010 calculated from 2009 data
(Source: American Community Survey, 5-year estimates)

Transportation within the Des Moines metropolitan remains primarily automobile based (DSM MPO, 2014). The amount of personal automobile travel is measured by the Vehicle Miles Traveled (VMT), which is calculated by taking the total number of miles traveled by all vehicles within the year for the region. When presented on a per capita basis, VMT can identify how much auto traffic is occurring. Despite the region still being heavily auto-dependent, VMT has fallen by 8.1% since 2008 (Table 2). Peak VMT occurred within the Des Moines metro area in 2004 and is projected to continue a downward trend into the future (DSM MPO, 2016).

Table 2: Des Moines MPO VMT Per Capita, 2008-2015

Year	*VMT per capita*	*Percent Change*
2008	105,000	n/a
2009	102,412	-2.5
2010	104,814	2.3
2011	101,069	-3.6
2012	102,736	1.6
2013	98,093	-4.5
2014	95,917	-2.2
2015	96,527	0.6
Total Percent Change 2008-2015		**-8.1**

(Source: Des Moines MPO VMT Report, 2016)

With falling VMT and the identification within regional plans for greater usage of other modes of transportation, public transportation plays an increasing role in connecting people to employment, recreation and educational opportunities. Within the Des Moines region, DART provided public transportation, through a public bus service and on-call shuttles. Within the Des Moines Metropolitan Area, 4.70 million rides were taken in 2016, a slight decrease since reaching a peak of 4.79 million in 2015 (Table 3). This has been partially attributed to the rise of ridesharing apps (Descant, 2017), but can also be partially due to changes in bus routes, which has increased the frequency of buses within areas of higher ridership and reduced service in areas further out (TMD, Inc., 2016).

Table 3: Annual Ridership on DART, 2012-2016 (Millions)

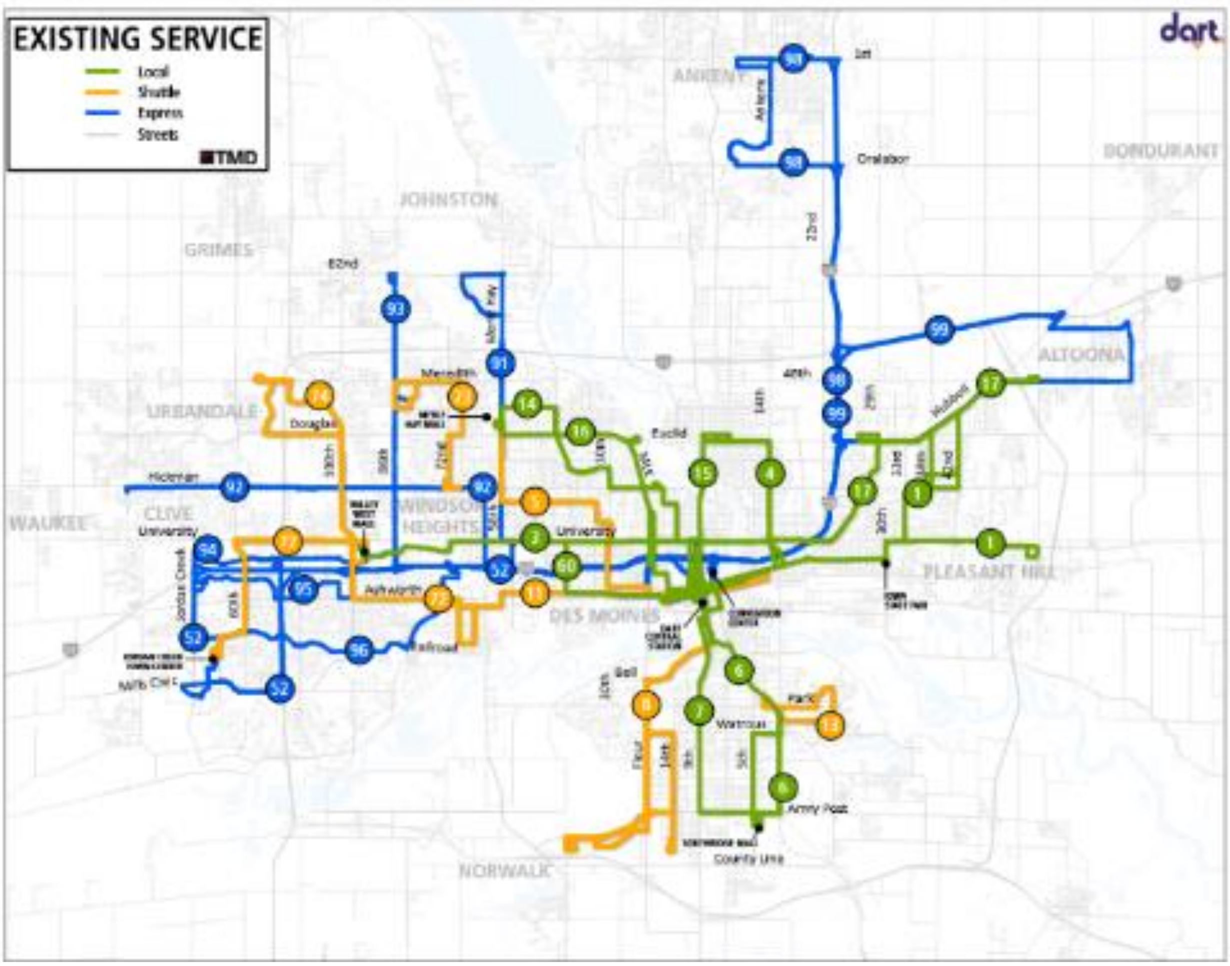
Fiscal Year	*Annual Passenger Miles*	*Unlinked Passenger Trips*	*Percentage Change of Passenger Trips*
FY 2012	32.9	4.57	n/a
FY 2013	33.9	4.44	-2.8
FY 2014	33.1	4.70	+5.7
FY 2015	33.4	4.79	+1.9
FY 2016	28.5	4.77	-0.4

Source: (National Transit Database, 2018)

DART has found, through internal surveys conducted in 2011, that most people ride their buses, because they need to get to their place of employment. Employers have noted in these surveys that they have difficulty retaining workers, due to the metro area's mismatch between housing and places of employment (TMD, Inc., 2011). This suggests that DART needs to find ways of connecting workers to their jobs, to better serve their riders. Part of ensuring that people have access to bus service is ensuring connectivity in the sidewalk network around the bus stops.

DART's bus routes are currently concentrated within the most urbanized parts of the metropolitan area (Figure 3). 15 routes focus on the city of Des Moines and the immediate suburbs as local routes. There is one additional local route that connects to major employment centers: Valley West Mall and Jordan Creek Town Center. Seven express routes operate to provide transportation to and from farther out suburbs into the downtown. Bus routes are important in connecting workers to employment opportunities, both downtown and in the suburbs.

Figure 3: DART Bus Routes, 2011



Source: (TMD, Inc., 2011)

2.2 PLANNING AND CONNECTIVITY IN THE STUDY AREA

Falling VMT, rising population, the need to access employment, and the issues surrounding climate change have been identified as factors within central Iowa that influence the need for greater investment in public transportation. These factors have been identified in regional plans and within plans for the city of Des Moines. The *Tomorrow Plan* is central Iowa's long-range planning document and its first goal is to: "Allow for sustainable alternatives that offer flexibility and that enhance mixed uses, walkability/accessibility, and sense of place through zoning, land use planning, and development" (DSM MPO, 2013, p. 14). Not only does the Tomorrow Plan discuss accessibility in terms of transportation options, the plan also identifies the need to reduce greenhouse gas emissions in order to mitigate the effects of climate change, noting that, "Choosing [...] alternative modes that generate fewer greenhouse gas emissions helps mitigate climate change and helps improve the health of the planet and residents (p. 151)." In support of the goals of the *Tomorrow Plan*, the Des Moines Area Metropolitan Planning Organization (MPO) created a regional transportation plan, *Mobilizing Tomorrow*. The primary goal of this plan is to "enhance multimodal transportation options" (2014, p. 4), which supports "a greater mix of transportation choices, including a robust transit network, an active carpool culture, and land use and design that support walkability" (DSM MPO, 2014, p. 8).

There have been many methods proposed on how to measure walkability (Talen, 2003; Sandalak, et al., 2013; Lee & Talen, 2014). One popular method is the Walk Score, available freely online (walkscore.com). Walk Score is a company that provides an online tool to evaluate the walkability of a city or neighborhood (Walk Score, 2011).[3] Although the Walk Score methodology

[3] The Walk Score is calculated by weighting nine different amenity categories, such as grocery stores, and applying distance decay function when the amenities are further than a quarter mile (Lee & Talen, 2014). The validity of the Walk Score methodology has been tested by independent researchers and found to correlate to greater pedestrian activity (Hirsch, Moore, Evenson, Rodriguez, & Diez-Roux, 2013). Des Moines currently scores only a 45 on the Walk Score across the entire city but shows great variability between neighborhoods. Carpenter, a small neighborhood near Drake University scores the highest, with a Walk Score of 78, whereas Chesterfield, an industrial area just north of the Des Moines River scores a 9. Improving the Walk Score of the city would not only be in line with the stated planning goals, it would also benefit people who are unable to use an automobile or cannot afford to own one, such as the poor, young people, and the elderly (Talen, 2003).

does not take into account sidewalks in its analysis, other studies have used sidewalks as a measure of walkability. A review of 25 studies on pedestrian indices built to assess walkability, 15 measures sidewalks in some fashion, and eight identified sidewalk availability or connectivity as a factor in walkability (Maghelal & Capp, 2011).

In 2016, the City of Des Moines launched a $500,000 walkability study of its downtown core to identify projects that would increase sidewalk connectivity and remove barriers to cyclists and pedestrians (Meinch, 2015). This effort is a part of two related plans the city is working on. The first is its 20-year plan, *PlanDSM*, which focuses on land use and a change to form-based zoning codes (DSM Community Development , 2016). The other is *MoveDSM*, the city's first transportation plan. *MoveDSM* looks to create a more diversified transportation system in Des Moines, by promoting public transit and walkability within the city (DSM Community Development, 2018). As of the writing of this report, the *MoveDSM* plan is still being completed and has not been released yet. Preliminary public engagement documents have been released however, and these documents contain sections focused on missing sidewalks (Development, 2018). *MoveDSM* presents a prioritization scheme of missing sidewalks based upon four criteria: distance from bus stops, distance from an elementary school, distance from a commercial node, and a connectivity value (the formula for which is not revealed in the public documents). Although all of these items are a good way to prioritize missing sidewalks, they miss a critical aspect in ignoring the social justice aspect involved in determining which areas need sidewalks the most. This professional report takes socio-economic variables into account, and hopefully these data can inform DART and other regional governments when it comes to the prioritization of missing sidewalks. Applying the concept of pedestrian accessibility to DART will allow them to create a better experience for their passengers, who will be able to more easily access bus stops.

3. LITERATURE REVIEW

In this literature review I focus on sustainability and public transportation, planning for social justice, and empirical studies on the links between walkability, public transportation, and planning for social justice. Within sustainability, I examine the effects of automobile dependency on climate change, and the positive impacts that public transportation can have on offsetting the effects of climate change. Planning for Social Justice looks at the link between the low-income population and the necessity of public transportation for these groups. Empirical studies focus on previous research that examined walkability, public bus systems, and low-income population, as well as techniques used to assess these conditions.

3.1 Sustainability and Public Transportation

Sustainability has been defined as "[…] development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland Commission, 1987, p. 31). Planners have the ability to influence sustainability in the plans that they create. Planning for impact urban form and transit planning are two the ways that planners can influence sustainability within a city.

Sprawl is a major contributor to climate change, by spreading housing, employment and retail across a broad geographic area, and then requiring an automobile to connect between them (Ewing & Hamidi, 2015). An example of the influence of urban form on levels of greenhouse gas emissions can be drawn by comparing Atlanta and Barcelona. Both cities have similar levels of per capita wealth. Atlanta is a very sprawling city, while Barcelona is compact. Atlanta produces six times as much transportation-related greenhouse gases as Barcelona (Rode, et al., 2014). This matters to planners because metropolitan areas continue to sprawl. A concerted effort by planners to plan for compact cities with public transportation and improved walking or biking infrastructure could lower greenhouse gas emissions by 20 to 50 per cent (IPCC, 2014).

Compact development is more sustainable for many reasons, but one of the main factors is that residents of compact areas take fewer trips via automobile. Compact infill developments reduce the total Vehicle Miles Traveled and residents of compact developments are more likely to walk, bicycle or take public transit, as opposed to driving automobiles (Nelson, 2017). Greater access to public transit and a walkable community make people less likely to use a car as their primary mode of transportation (Buehler & Hamre, 2015).

Public transportation has been identified as more sustainable than private automobile ownership in numerous studies (Rode, et al., 2014). Use of automobiles within cities is the largest single contributor to greenhouse gas emissions. The same research study has found that greenhouse gas emissions are much lower per capita when people use a well-connected public transportation system. Public transportation is usually more accessible within dense urban environments, and having land uses spatially closer makes public transit more efficient in time and energy usage. Additionally, dense areas typically have better pedestrian and bicycling infrastructure that encourage the use of non-motorized modes (Buehler & Hamre, 2015).

In summary, sprawling metropolitan areas are not sustainable as they create a much greater carbon footprint due to increased automobile usage. Planners can work to shift patterns of development by promoting connectivity of pedestrian infrastructure and public transportation. Focusing on these areas will increase sustainability and also equity

3.2 Planning for Social Justice

The link between equity and sustainable development is not a new one.[4] The "aspiration for a better life" for all people identifies that within the concept of sustainability there is a need for social equity. Cities that want to be sustainable are looking for ways of enhancing social justice for all of their residents. Enhancing the quality of public transportation is a very tangible way of increasing opportunities for access to education, social services, and employment.

[4] The original Brundtland Commission, convened in 1987 at the behest of the Secretary General of the United Nations in order to study sustainability, reported that: “Poverty is not only an evil in itself, but sustainable development requires meeting the basic needs of all and extending to all the opportunity to fulfill their aspirations for a better life” (p. 3).

Non-rural poverty in America is also more concentrated in cities, where 19% of people are poor, as opposed to suburbs, where 7.5% of the population is poor. One of the main factors contributing to the poor living in cities is access to public transportation, which in turn gives them access to education, employment and government services (Glaser, Kahn, & Rappaport, 2008). Central Iowa follows a similar pattern. Poverty in Des Moines is concentrated around the central business district, specifically on the east side, with smaller pockets on the northern side of the city within the neighborhoods of Drake and Riverbend (Peters, 2011).

Not only are low-income individuals more likely to use public transportation, they are more likely to rely on it as a primary means of transportation, as the costs of owning, operating and maintaining an automobile are often prohibitively expensive (Glaser, Kahn, & Rappaport, 2008). Low income individuals are also more likely to walk as necessary transportation (Cerin, Leslie, & Owen, 2009). Having a well-connected sidewalk network is important for people that must walk to their daily needs, but in a low-density metropolitan area like Des Moines, being able to walk to public transportation, being able to get to the bus stop, is equally as important.

To enhance social justice, planners should work to increase access to public transit within low-income areas (Fainstein, 2010). Within the Des Moines area there is mismatch between housing and jobs, as previously noted, which causes low-income individuals to spend more resources on transportation (TMD, Inc., 2011). One of the goals noted within the *DART Forward 2035* Plan and the *Tomorrow Plan* is to increase access to jobs in Central Iowa (DSM MPO, 2013; TMD, Inc., 2011). Investments in public transportation and walkability would significantly work toward the goals of these plans and enhance social justice in central Iowa.

In summary, planning for equity is an important part of sustainability. The people who either cannot afford an automobile, or cannot operate one, need reliable access to public transportation as well, to have a chance to improve their socio-economic condition. Part of access to public transportation is increasing the quality of the built environment around bus stops. Connectivity of the sidewalks is important for this purpose, as it allows people the most direct route to their stop and provides a more pleasant experience to them.

3.3 Empirical Studies

Other Midwestern cities have conducted walkability studies in support of pedestrian master plans that consider the sidewalk network within their cities. The Walkability Plan for Kansas City identifies incomplete sidewalk networks as being a barrier to pedestrian activities. The plan notes that gaps in sidewalks and discontinuous sidewalks affect a person's decision whether to walk or not. Kansas City, being a large city, in terms of land area, identified that there was considerable un-evenness in the distribution of sidewalks, with downtown having the greatest connectivity, while outlying areas of the city, especially to the north, had low connectivity (Lea Associates, Inc., 2003).

Minneapolis is another regional city that has a specific pedestrian plan. Minneapolis completed its Pedestrian Master Plan in 2009 and identified completion of the sidewalk network as its number one goal in promoting pedestrian activity. In studies conducted in support of the plan, it was found that most of the city had a completed sidewalk network (93%), but that some barriers still existed due to rivers and industrial areas (City of Minneapolis Public Works Department, 2009). Minneapolis also identified walking as being a critical part of access to public transportation, and that the built environment around transit stops should be created to enhance the ability for people to easily access it on foot. This was tied to the idea of equity, noting that walking is the "only mode of transportation universally affordable to everyone (p. 17)."

City planning departments have not been the only ones to examine the link between sidewalks and public transit. Academic studies have also looked at the link between sidewalk connectivity and public transportation in more depth. A study, on the Metro Orange bus line in Los Angeles, found that sidewalk connectivity was more important than the state of repair of the sidewalk, when controlling for the socio-economic characteristics of the surrounding neighborhood (Woldeamanuel & Kent, 2015). They first defined their analysis area, as being within a quarter mile of the bus stations. Using Geographic Information Systems, they buffered that distance to define their study area. To determine the Quality Index, they utilized field observation and developed a quality model of bad, medium or good sidewalks. From these data they were then able to calculate the state of repair for each the sidewalks around each bus stop.

To create the connectivity index, Woldeamanuel and Kent, first created a potential connectivity index, which would be the theoretical extent of the sidewalk infrastructure, were it to be build out on both sides of all roadways. They then compared these two data points, the actual connectivity versus the potential connectivity to determine a connectivity index for each of the bus stops. To control for socio-economic characteristics around the bus stops, they used census tract data for all tracts that fell within the buffered walkshed. They found that connectivity is more important than the quality of the sidewalk on the impact of ridership at a given bus stop (Woldeamanuel & Kent, 2015).

These studies show that a well-connected sidewalk network can increase ridership at bus stops and enhance the access that people have to public transportation. Previous sidewalk studies have involved researchers conducting on-ground visual inspections of the sidewalk infrastructure (Frackelton, et al., 2013; Galanis & Eliou, 2011), but these have focused on city centers and more small-scale areas.

Manually digitizing sidewalk data and combining that data with existing sidewalk data is a time-consuming activity (Kang, Scully, Stewart, Hurvitz, & Moudon, 2015). Rather than manually digitizing, aerial imagery can be used to identify sidewalk features and automatically digitize them into usable data. Imagery from satellites or airplanes is more commonly used to study things such as deforestation and urban sprawl (Weng, 2011), but has also been used to determine more fine-grained features, such as sidewalks or parking spaces with urban environments (Mattyus, Wang, Fidler, & Urtasun, 2016). What is not covered in the literature is a practical way that local planners can put these methods into practice using the tools at their disposal.

In summary, previous methods for identifying missing sidewalks have generally relied upon either field research or manually digitizing the sidewalk features from aerial photographs. When the literature has proposed automated methods for sidewalk detection, these methods are technical and difficult to implement on a practical level with the tools that local planners have available to them. The methodology presented in the following section presents a practical way that local planners can identify and prioritize missing sidewalks to enhance the connectivity of their pedestrian networks.

4. METHODOLOGY

This section describes the methodology used to conduct the sidewalk connectivity study for DART. The first part of this section covers the data used to conduct the study and an overview of the computer software used analyze the data. Next follows a discussion of the methods used, covering the steps of Identifying Missing Sidewalks, Exploratory Spatial Data Analysis, Automation, and Validation. Each of these steps was covered in greater detail and will allow for a researcher or planner to recreate the process described in this report.

4.1 Data

To determine where missing sidewalks occurred in the study area and identify the priority for providing those missing sidewalks required the use of many different sources of data. To determine the locations of missing sidewalks, a raster file containing an aerial image of Polk County, Iowa was obtained from Polk County and the roadway centerline data was obtained through the Des Moines Regional GIS portal. The data used to identify areas of need, including ratio of income to poverty, percentage non-White and percentage with Graduate Degrees was obtained through the American Community Survey of 2016. Census Block Groups were the spatial unit utilized. Data on bus stops and shelter locations came from DART. Additional data used to visualize the study area, such as municipal boundaries and neighborhood boundaries within Des Moines, also came from the Des Moines Regional GIS portal. These data are discussed in greater detail during this section of the report.

In 2018, DART provided shapefiles, a type of computer file that stores geospatial data, which contain information on the locations and attributes of bus stop sites. DART also wanted to prioritize areas that have shelters installed at the bus stop, as bus stops with shelters represent a higher level of investment for DART. The bus stops shown in the Figure 4 are those that fall within the municipal boundaries of Des Moines, as well as quarter miles access distance from the bus stop. For this study, a quarter mile (approximately 400 meters) was used to define the walkable distance that people are willing to take to the bus stop. A quarter mile is often used within the literature as a measure of how far people are willing to walk to access transit (Woldeamanuel & Kent, 2015).

Figure 4: Bus Stops in Des Moines, 2018

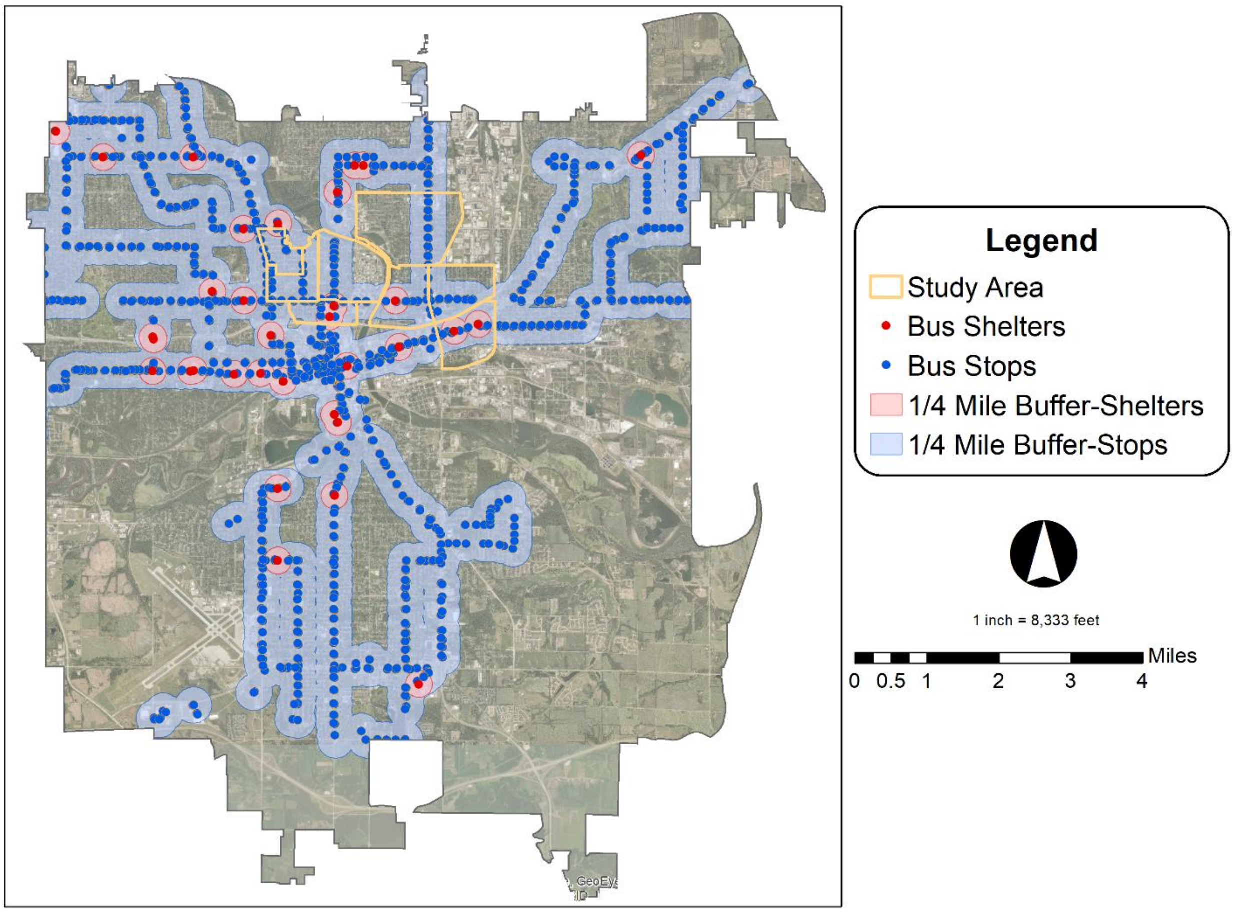
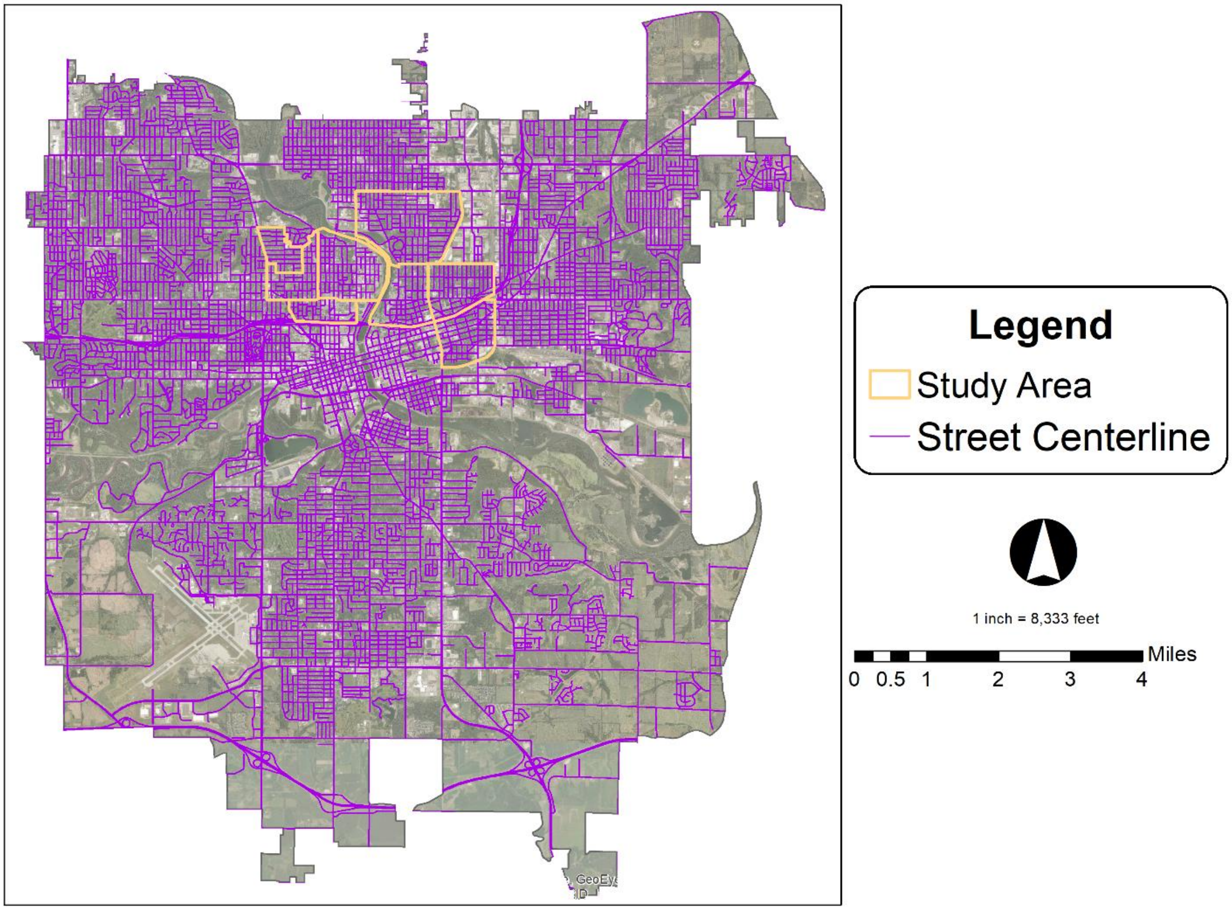
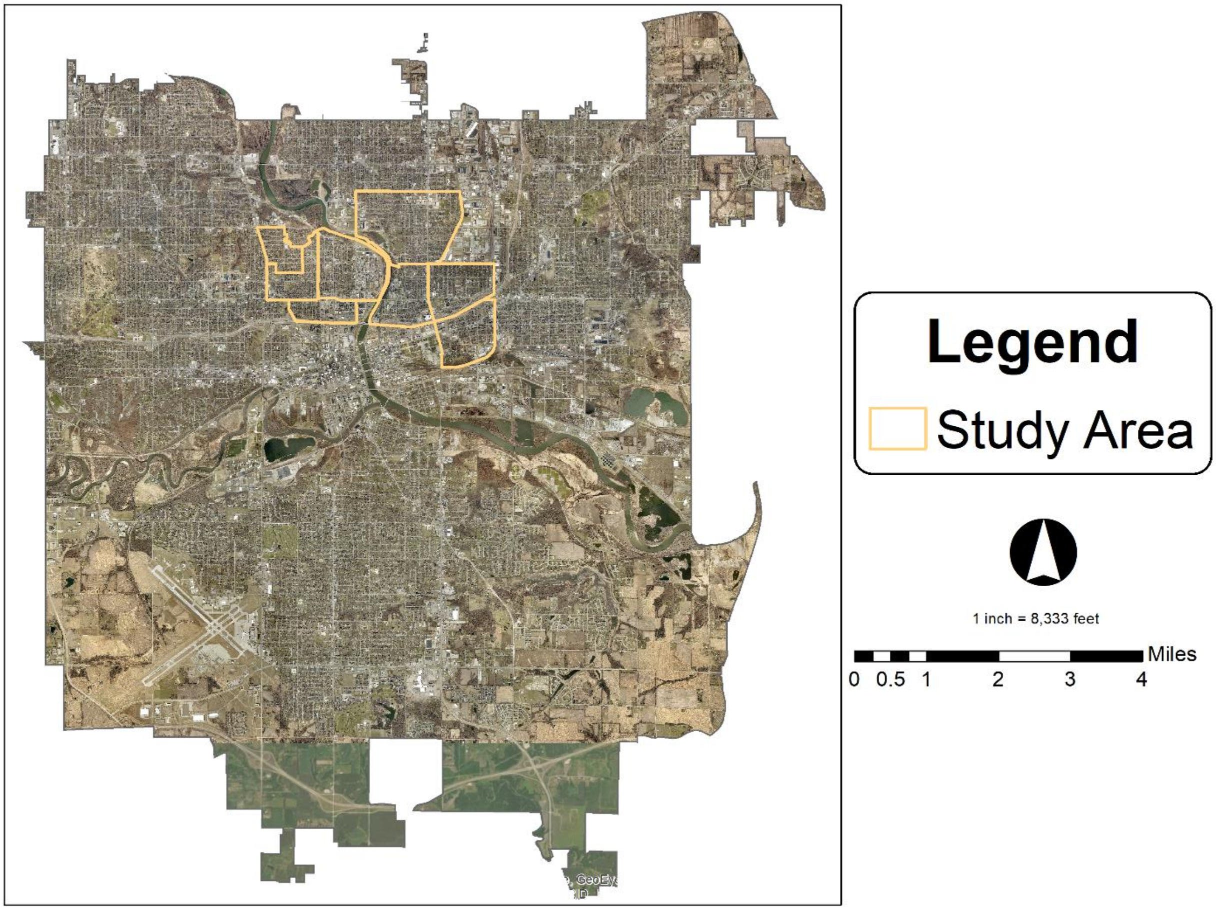


Figure 5: Street Centerlines, 2017



The Regional Geographic Information Systems (GIS) database, managed by the City of Des Moines, provided shapefiles for the roadway centerline data (Figure 5), and county and municipal boundaries. Roadway centerlines were used to identify the search area in which a sidewalk can occur.

Figure 6: Aerial Imagery, 2017



Aerial Imagery refers to photographs taken from the air, which are then corrected for the angle of the aircraft, so that when viewing the photograph, it appears to be taken over the ground. This imagery gives an accurate representation of the ground as viewed from the air. In order to reduce tree canopy and other vegetation interfering with the observation of sidewalks, winter imagery is preferable to summer imagery. The imagery used in this study was obtained from Polk County from the winter of 2017 (Figure 6). This imagery consists of a raster file in a ".sid" format, with an uncompressed size of 514 GBs. The file is expected to be so large due to the high level of detail of the image. The cell size of the image is 0.32 by 0.32, which is the equivalent of 1 foot (0.3048 meters) by 1-foot resolution. This gives a high enough resolution to be able to distinguish fine-grained features, such as sidewalks, therefore being adequate for the purpose of this study. The aerial imagery is stored in three bands, which represent different wavelengths of light. These bands correspond to the wavelengths of Red, Green, and Blue visible light. The composite of these bands, the aerial image, thus shows up as a true-color image, much how one would expect if viewing the ground with the naked eye.

Data that illustrate the socio-economic conditions within the study area identifies areas of need. Data from the American Community Survey (ACS) were used to quantify Socio-Economic Status within the study area, using the variables of 125% of the poverty rate, percentage non-White, and percentage with Graduate Degrees. These three variables will identify the block groups that are areas of need. The census block groups are the area of analysis due to block groups being the smallest geographic unit at which income levels are tracked by the Census Bureau. Block groups are combinations of the census' blocks, which are created by local partners and the Census Bureau and trusted to represent distinct neighborhoods or areas of a community (Peters, 2011, p. 16).

When discussing poverty within the context of the United States, it is important to define what is meant by poverty and how it is statistically defined. The United States Census Bureau defines poverty by defining an income threshold for household by size of the household. Any family that falls below the threshold set by the Census Bureau has all members of the family considered to be in poverty (U.S. Census Bureau, 2017). However, people who are above the Census Bureau's official poverty level may still be in need of assistance in meeting their daily needs. For this reason, the US Department of Health and Human Services issues poverty guidelines each year, which are higher than the Census Bureau's poverty thresholds (U.S. Department of Health and Humand Services, 2015). The poverty guidelines expand the amount of people who qualify for government assistance, such as Medicaid or Women, Infants, and Children (WIC). In conducting research on poverty, the U.S. Census Bureau provides the most comprehensive set of statistics but does not record the poverty guidelines issued by Health and Human Services. For this reason, it is necessary to use the 125% of the Census Bureau's statistics on poverty. The 125% of the poverty rate captures those individuals eligible to receive government benefits to assist those in poverty (Fisher, 1992).

The variable "Percentage Non-White" is used to identify areas of the city that have high minority populations. Based upon a survey conducted in 2016, ridership on public transit is taken disproportionately by minorities. For example, African Americans are approximately 13% of the population of the United States, yet they account for 24% of ridership on public transportation (APTA, 2017). For this study, the variable “Percentage Non-White” was calculated by taking the total population of the block groups and subtracting the “White, Non-Hispanic” from the total, based upon data from the American Community Survey, 2016.

The variable "Percentage with Graduate Degrees" is used to assess the education level within block groups. The survey mentioned previously, found that 51% of people who take public transportation have a bachelor’s degree or some graduate schooling, whereas less than 8% of people who take public transportation in the United States have only a High School Degree or less (APTA, 2017). For this study, persons with a Graduate Degree (Master’s or PhD) or a professional degree (Medical Degree or Law Degree) were combined, based upon data from the American Community Survey, 2016. Identifying areas with the highest number of people with graduate degrees helps to determine the areas of less need.

Finally, the software used in this study includes ArcMap and GeoDa. ArcMap 10.6 is the primary software used in this study. ArcMap is an application for GIS, which allows for the display, processing and analysis of geospatial data (ESRI, 2012). ArcMap, and the related suite of programs, are the most common software available for geospatial analysis for planners. For this reason, it is useful to develop techniques, procedures, and models in this software, so that they can be replicated by other planners. ArcMap has a great deal of functionality, not only in the tools available within the software, but also due to its integration with the Python programming language. With Python, new tools can be created and layered in such a way as to automate complex workflows. The other software that also was used is GeoDa, which is designed to conduct Exploratory Spatial Data Analysis (ESDA) used to identify areas of need.

4.2 Descriptive Statistics

Looking at the descriptive statistic of the variables for the block groups within the city of Des Moines presented findings that shed light on the ESDA results described later in this section. This section will examine the three socio-economic variables across the city of Des Moines, with emphasis placed on the descriptive statistics within the study area. This section underscores the findings of the ESDA and gives a background though which to interpret later findings. The statistics in this section are derived from the block group level. However, it is difficult to discuss data at the block group level without reference to an aggregate scale. Since Des Moines divides itself into neighborhoods, and these neighborhoods are part of the colloquial vocabulary when talking about the city, thus these neighborhoods are used in this section as a reference point when discussing the socio-economic variables. Where any block group overlapped more than one neighborhood, the block groups was considered to belong to the neighborhood in which a majority of the block groups fell. A map of the neighborhoods of Des Moines can be found in Appendix F.

When looking at the Percentage of Graduate Degrees or higher held in Des Moines, the minimum found is zero. This is true for 30 block groups, out of the 186 within the city. The greatest percentage found was 34.1%, found in the Westwood and Linden Heights neighborhoods, traditionally the tonier part of the city. The mean citywide is 7.1%, which is below the average for all of Iowa at 8.7% (US Census Bureau, 2016). Percentage of Graduate Degree holders had the lowest standard deviation (0.075) demonstrating that block groups tend to be closer to the mean with a tighter distribution.

For the Percentage at or below Near Poverty, the minimum for any block group was zero, due to the airport being its own block group, which has no permanent dwellings. Two other block groups, one in Merle Hay and one in Southwestern Hills also report no one in poverty. The lowest percentage above zero is 0.9%, which is located on the western side of the city in Waterbury. The block group with the highest Percentage near Poverty (72.2%) is located in a section of the city without an official neighborhood designation, just north of the Watrous Heights Neighborhood.

The next highest block group is the one that contains the Oak Ridge Apartment complex. Locate just east of Sherman Hill, this complex is home to a large refugee population. The mean for Near Poverty is 24%. On average a block group will have almost of quarter of its population near or below the poverty level. The standard deviation for poverty, however, is the highest of any variable looked at in this study. This implies that there is a degree of income segregation within the city of Des Moines.

With regards to the Percentage that is Non-White, like with the other variables, the lowest percentage was zero. The next lowest percentage (1.4%) is located between the Merle Hay Mall and Herbert Hoover High School on the northwestern corner of the city. The block group with the highest percentage (92.2%) is located in Mondamin Presidential, just south of Broadlawns Medical Center. The mean for the city is 28.9%, just under a third. The standard deviation (0.219) implies that there is slightly less ethnic and racial segregation between Whites and Non-Whites than income segregation, but much greater segregation then between those with and without graduate degrees.

Table 1: Descriptive Statistics of Socio-Economic Variables for Des Moines, 2016

	Minimum	Maximum	Mean	Standard Deviation
Percentage Graduate Degrees	0 (0)	34.1	7.1	0.075
Percentage Poverty	0 (0.9)	72.2	24	0.240
Percentage Non-White	0 (1.4)	92.2	28.9	0.219

The neighborhoods within the study area demonstrate lower mean for graduate degree attainment than the city (2.8% vs. 7.1%). The study area also has a greater mean for the percentage of its population at or near poverty (38.5% vs. 24%) and a much greater mean percentage of the population that is Non-White (60.4% vs 28.9%). Within the study area, the standard deviation for graduate degrees is lower (0.021 vs 0.075), due to a much smaller percentage of the population holding graduate degrees. The standard deviation for the percentage near poverty is also much lower (0.127 vs 0.24). The standard deviation for percentage Non-White however is greater than for the city (0.221 vs 0.219)

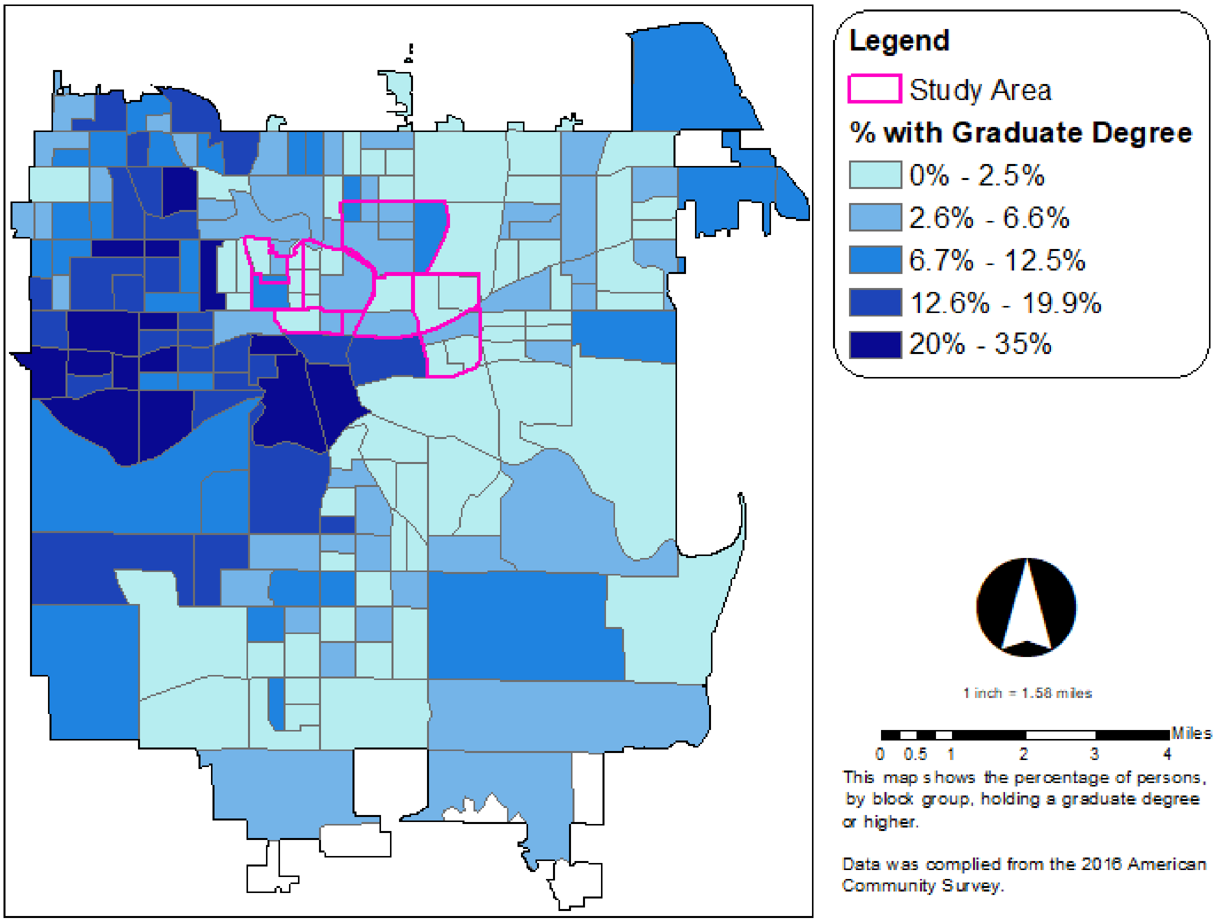
Table 2: Descriptive Statistics of Socio-Economic Variables for Study Area, 2016

	Minimum	Maximum	Mean	Standard Deviation
Percentage with Graduate Degrees	0	7.1	2.8	0.022
Percentage Poverty	11	59.6	38.5	0.127
Percentage Non-White	19.7	92.2	60.4	0.221

Moving from the descriptive statistics tables, the following choropleth maps visually illustrate the data that have already been discussed and show patterns in the data across the city.

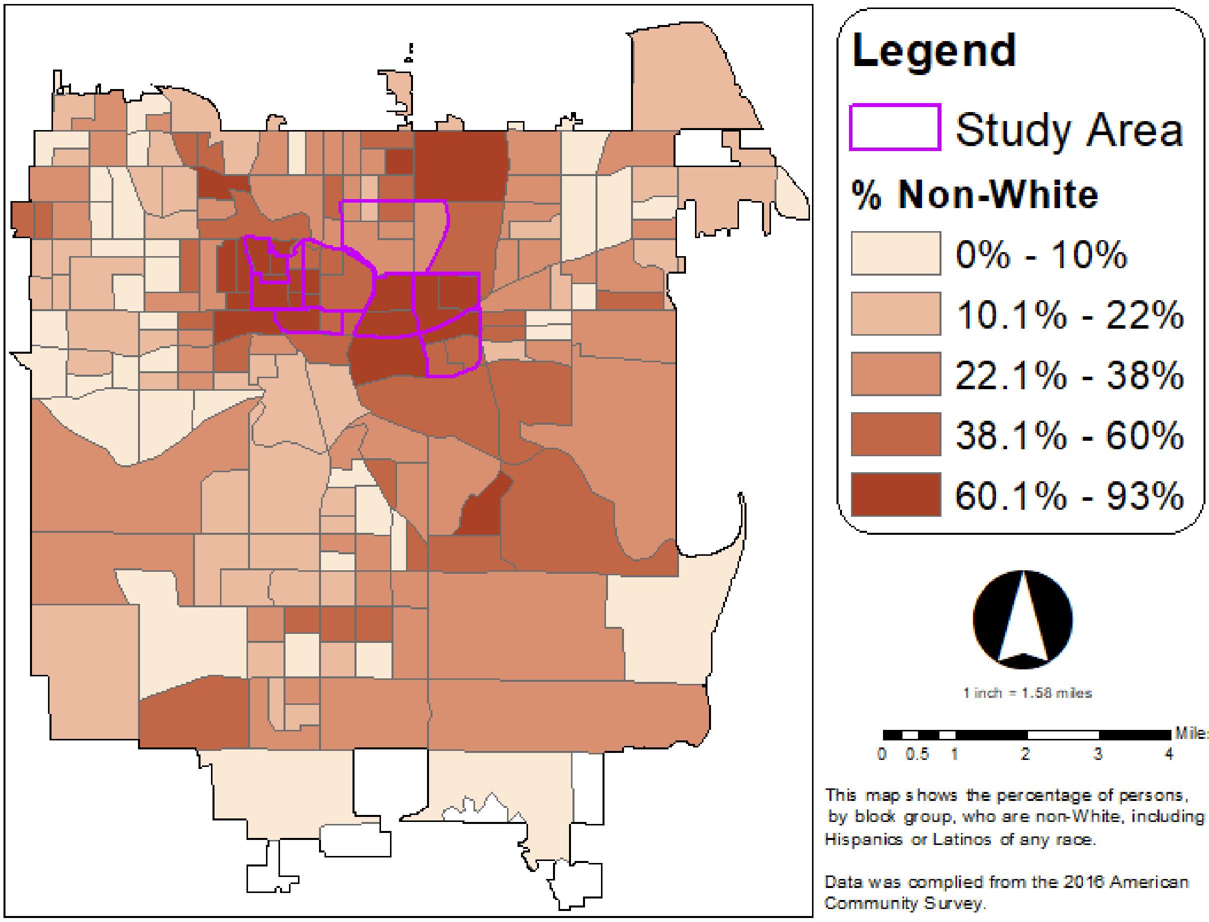
The areas with the highest percentage of people with graduate degrees occurs in the western part of the city. The highest block group, with 34% of people holding a graduate degree, occurs near Linden Heights and Westwood. Areas with greater than 20% of the population holding a graduate degree occur in downtown, the northern section of Sherman Hill, the residential area west of downtown, and due west of the Drake Campus, in Drake and Beaverdale. There are 30 block groups throughout the city where no one holds a graduate degree. These block groups include two block groups east of Drake, on split between Mondamin Presidential and Drake, and the other in Cheatom Park. Four occur in Highland Park. One in Capitol East, three in Fairgrounds. Fourteen are found throughout the southern part of the city. Areas where less than 10% of the population have graduate degrees occur on the east and northern parts of the city, with another grouping in the Merle Hay neighborhood.

Figure 7: Percentage Graduate Degrees by Block Group, 2016



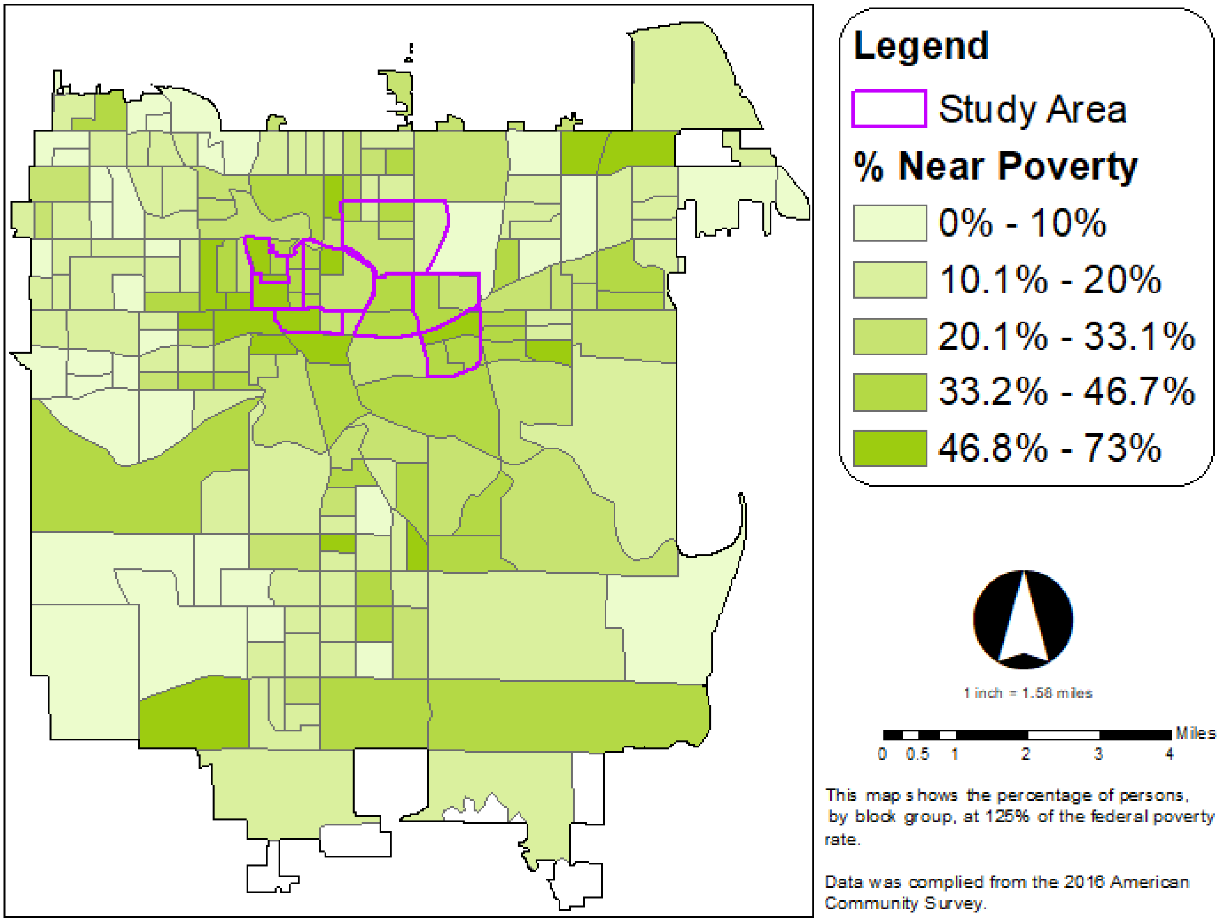
Areas with a high Non-White population occur in the center north part of the city, around Drake University, including the neighborhoods of Drake, Mondamin Presidential, King Irving, and Cheatom Park, and on the eastern side of the river, in the East Village, Capitol Park, Martin Luther King Jr. Park, and Capitol East. Of the 10 block groups with the highest percentage of Non-White residents, eight of them occur within the study area. One occurs just west, in the Carpenter neighborhood, and one exists in the south, in Prospect Park. The five highest Non-White block groups are located within the study area. They are located in Mondamin Presidential, King Irving, River Bend, and Martin Luther King Jr. Park and have a range of 84.4% to 92.2% Non-White.

Figure 8: Percentage Non-White by Block Group, 2016



Poverty occurs throughout the city, with a mean of 24%. Areas with a high degree of poverty occur within the study area, with five block groups having almost half of their population in poverty. The lowest poverty rate for any of the block groups in the study area is 31%, located in the River Bend neighborhood. Throughout the city, many of the block groups with high poverty rates are located near Drake University. Two block groups with over 46.8% poverty occur in the north east, one in the Fair Grounds neighborhood, one just south of the Airport, one in South Park, and one just north of Watrous Heights, in an area of the city that does not have a neighborhood organization.

Figure 9: Percentage Near Poverty and Poverty by Block Group, 2016



The next section of this report will describe the design of the study and how the data presented in this section were integrated with the software to produce an understanding of where sidewalk connectivity was lacking within the study area. The next section will lay out how missing sidewalks were identified, how areas of need are defined and identified, and how missing sidewalks are prioritized based upon areas of need and their relation to bus stops.

4.3 Methodological Steps

This section covers the steps taken to determine where missing sidewalks occur within the study area, and to prioritize those missing sidewalks, so that connectivity in the pedestrian network can be enhanced. These steps include Identify Missing Sidewalks, conduct Exploratory Spatial Data Analysis, and conduct Automation and Validation (Figure 10).

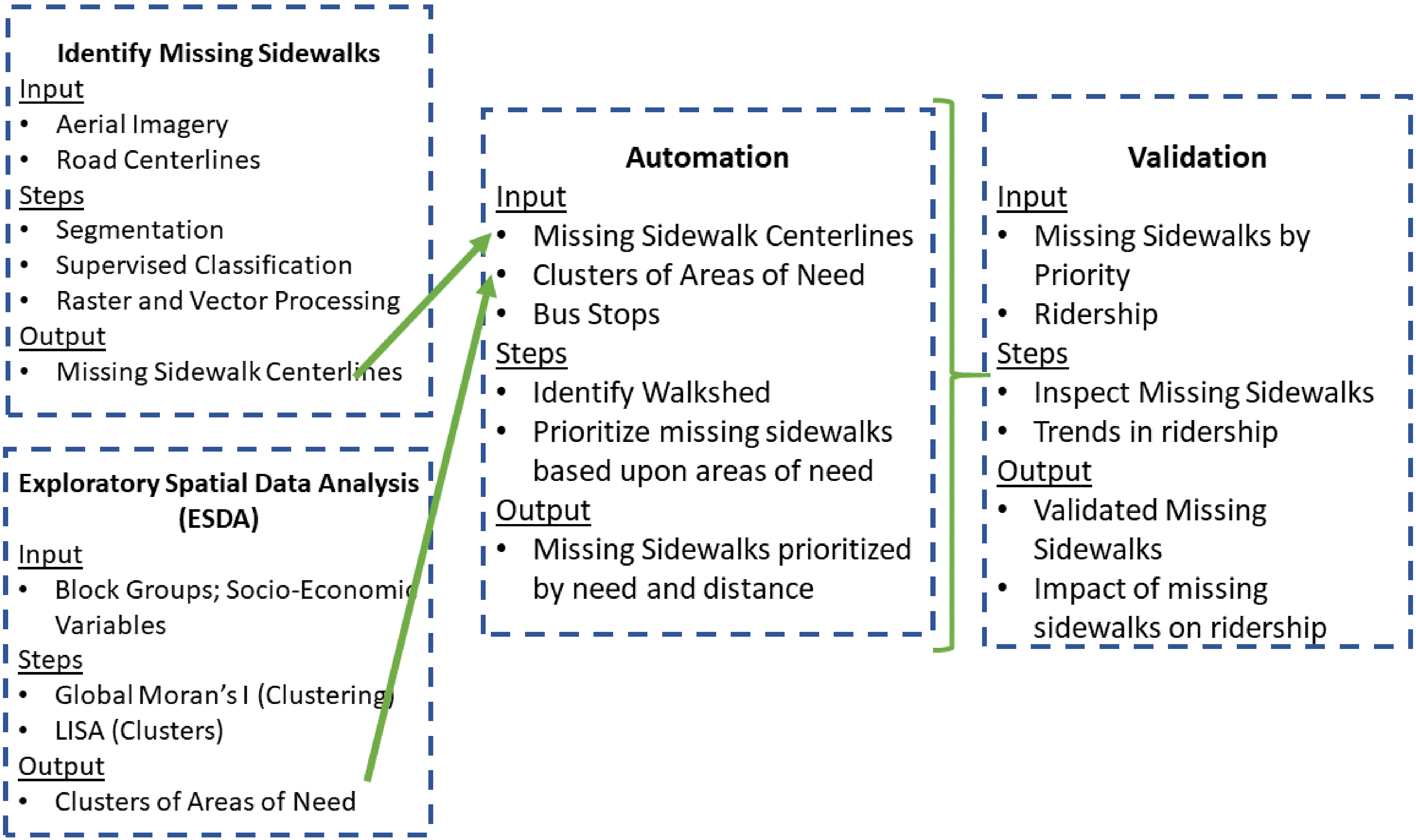
Identifying the Missing Sidewalks involved segmenting and classifying the aerial imagery to differentiate land covers and creating models, which would process the raster and vector data into a layer that showed extant sidewalks. Roadway centerlines were then used to create a search area from the classified imagery, in which sidewalks could occur. The resultant search area was then processed to extract the land uses which correspond to sidewalks. The raster data of the sidewalk imagery was then converted to vector data. A line feature of the entire potential sidewalk network was created, and then the portions of the line feature that overlapped with the extant sidewalks was deleted, leaving a layer containing missing sidewalks.

The Exploratory Spatial Data Analysis (ESDA) step then focused on the three socio-economic variables (Percentage Graduate Degree, Percentage Non-White, and Percentage near Poverty) at the block group level, to determine if there was a global trend with these data, showing clustering. Then Local Indicators of Spatial Autocorrelation (LISA) was run to identify the block groups that had High levels and bordered other block groups with High levels for the Percentage Non-White and Near Poverty. In the case of the Percentage holding Graduate Degrees the Low block groups that bordered other low block groups was used. Combining the block groups from these three variables revealed neighborhoods that had higher levels of need than other parts of the study area.

The step of Automation involved the creation of a Python script, which assigned a rank to the missing sidewalks based upon the block group's socio-economic variables identified in the ESDA step, as well as the distance that a given missing sidewalk was from either a bus stop, or a bus shelter.

Finally, using open source data from GoogleMaps and GoogleStreetview, validation of the identified missing sidewalk segments was conducted. This step identified if the missing sidewalks were truly missing, and whether there were any issues with the models used in identifying the missing sidewalks. Ridership data for each bus stop was symbolized as to whether it fell above, or below the mean ridership for the entire DART system. The ridership for stops was compared to the missing sidewalks to see if any trends emerged.

Figure 10: Methodological Steps



4.3.1Identifying the Missing Sidewalks

To identify the missing sidewalks, I used a high-resolution aerial photo, a line feature containing street centerlines, and the processing tools available in ArcMap 10.6, particularly the spatial analyst toolset. This step involves raster preprocessing, segmentation, classification, and creating models to generate missing sidewalk line features.

4.3.1.1 Raster Pre-Processing

A raster file is a file that contains rows and columns of pixels, which store data, much like a digital photograph. Since this study uses aerial photography, raster data is the first type of data to process. The initial raster file covered all of Polk County, IA, and contained a little over half a terabyte of data, which was too large to conduct any processing. The Extract by Mask tool was used to extract the section of the raster that fell within the borders of Des Moines. The output of the Extract by Mask was a smaller raster covering only the area of Des Moines. This raster was still too large for direct processing, so a “fishnet” was constructed using the Create Fishnet tool. A fishnet is a grid of line features that can be generated in ArcMap. The fishnet contained a grid measuring 5x5, which, when used to split the raster of Des Moines, created 36 smaller tiles, each consisting of about 2 gigabytes of data. These smaller tiles could then be further processed during the next step of segmentation.

4.3.1.2 Segmentation & Classification

Segmentation is a process that utilizes a mean-shift approach to simplify a detailed image into a smaller number of segments, in order to have the classification run more smoothly (Rougier & Puissant, 2014). The Segment Mean Shift tool in the Spatial Analyst tool box is how this process is run in ArcMap. What this tool does is "look at neighboring pixels and groups them together if they share the same spectral characteristics" as well "eliminate the salt and pepper effect that you sometimes see in classified maps and to produce a clean classified image (ESRI, Inc., 2015)."

There are three parameters within the segmentation tool that control the level of detail created by the segmentation: Spectral Detail, Spatial Detail, and Minimum Segment Size (ESRI, 2017). Spectral Detail determines how much weight is given to spectral differences between pixels on a scale of 1-20. More segments were created the closer to 20 that this parameter is set. In this study, I set the Spectral Detail to the highest setting, 20, in order to better differentiate areas of similar spectral characteristics as are often found in city environments. The Spatial Detail parameter scale also ranges 1 through 20. Selecting a higher value of this parameter results in the classification giving more weight to how close a given pixel is to another similar pixel. To gain the level of detail needed to differentiate the spectral characteristics of a city; this parameter was set to higher detail levels. The final parameter is the Minimum Segment Size in Pixels. This parameter is set to avoid having small pixels interrupting the desired segments. Once these variables are appropriately selected, the segmentation is run in ArcMap. The result is an image with reduced spectral details, which will improve the accuracy of the classification.

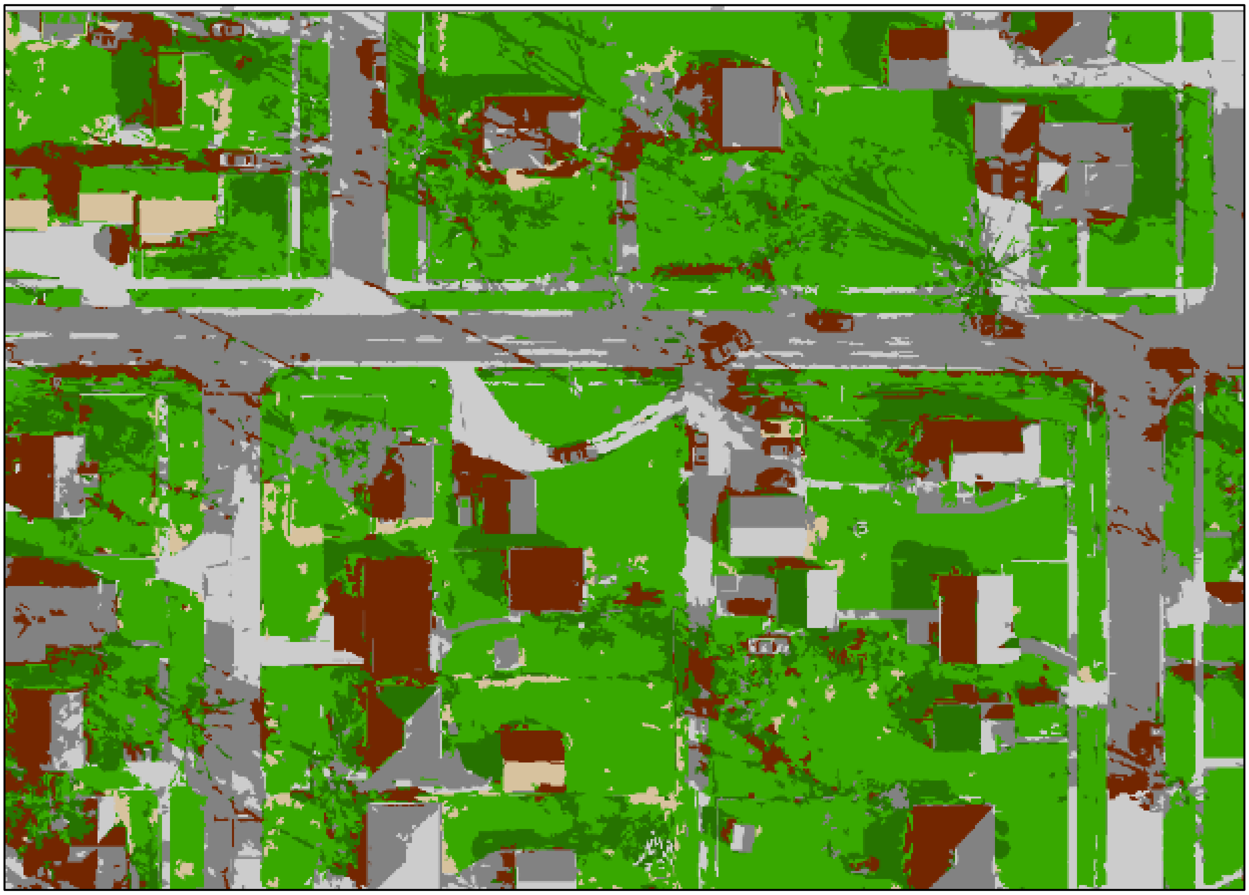
Figure 11: Example of Before and After Segmentation

Once the images were segmented, classification could then be conducted. Classification is a process that uses an algorithm to divide a raster image into discrete spectral classes. There are two main types of classification: Unsupervised and Supervised. Unsupervised uses the Iso Cluster algorithm to identify spectrally similar parts of the raster, based upon the input number of classes, and automatically produces a signature file (.ecd) that is used in the classification. The benefit of Unsupervised Classification is that it does not require manual selection of training sites, thus saving time. However, this method proved unsatisfactory due to its inability to separate sidewalks from rooftops, and the tendency for other features to be merged into similar classes.

The supervised classification divides the imagery into different land use types, such as roofs, grass, trees, water bodies and concrete.[5] Supervised classification requires that the signature file (.ecd) be manually created. The signature filed is created through the Classification tool bar in ArcMap. Located in this tool bar is the Training Sample Manager. The training sample manager allows for the selection of sites, saved as a shapefile, in the raster, which was used to build the signature file. These training samples are selected in order to define the spectral properties of each desired land cover. Initially 7 different categories were selected Street, Sidewalk, Grass, Tree, Roofs, Bare Earth, and Water. Samples were taken in sections of the raster that best typified a given land cover. Training sites were selected for each of the rasters and for each of the land covers. 14 sidewalk samples were taken, 7 for street, 25 for grass, 18 for rooftops, 4 for bare earth, and 4 for water. If in the generated classified raster, an area was classified improperly, it was selected and input as a new training site in the appropriate category. This process was repeated a minimum of four times for each raster in order to produce a useable classified image.

[5] Supervised classification is a method of breaking a detailed image down into different classes, based upon the spectral properties of the image by selecting training sites, as opposed to have a computer algorithm sorting the image, as occurs in an unsupervised classification (Churches, Wampler, Sun, & Smith, 2014).

Figure 12: Example of Classified Image



Once training sites were selected, it was time to create the signature file. This is accomplished by taking the shapefile generated by the Training Sample manager and inputting it along with the segmented image into the Train Support Vector Machine Classifier. The Support Vector Machine (SVM) is a new classifier that is good for handling large images and "is less susceptible noise, correlated bands, and an unbalanced number or size of training sites within each class" (ESRI, Inc., 2016). The output of this process is the signature file (.ecd) that is used to create the classified image. This file is then used an input for the raster classification, along with the segmented image. This produces a raster that then has pixels of only 7 different values, corresponding to the training samples.[6]

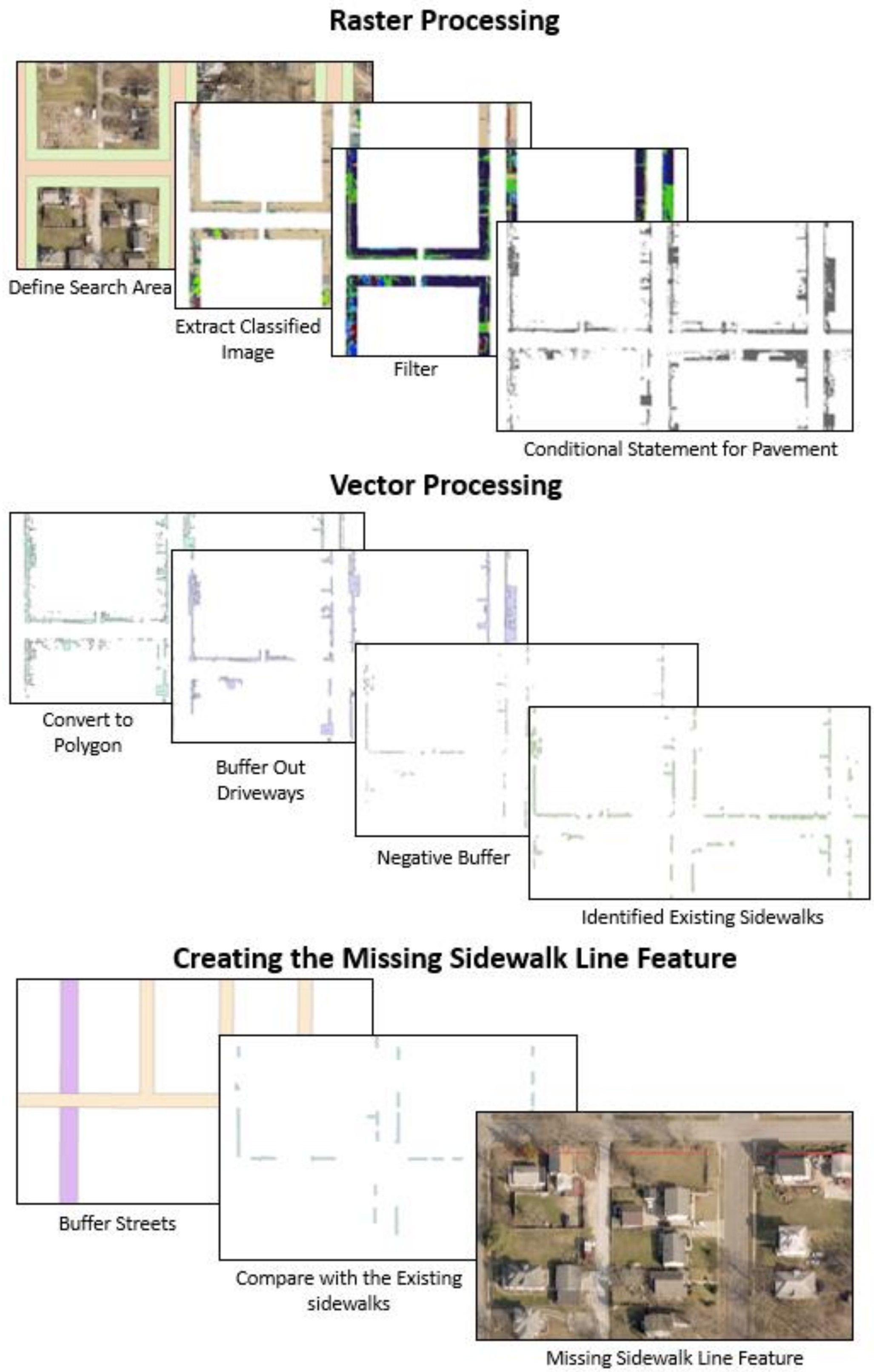
[6] One note when creating the output for a classified image. When saving the file name of the classified image, be sure not to save it beginning with a number, otherwise this will create a raster with no attribute table.

Once the training samples are created, it is then time to classify the image. There are many different classification algorithms available in ArcMap, but the Support Vector Machine was the preferred algorithm for this study, due to its ability to handle more detailed imagery compared to the other classifiers. Training samples were loaded into the Support Vector Machine classifier, which will generate the ".ecd" file that was used to conduct the classification. Once the ".ecd" file is created, the "Classify" tool was used, applying the ".ecd" filed to the segmented image from earlier (ESRI, 2017). The result of this was a fully classified image, showing the different land use categories.

4.3.1.3 Missing Sidewalk Centerlines

Creating a usable sidewalk line feature from an aerial photograph is a multi-step process, which can be broken down into three phases: Raster Processing, Polygon Processing and Line Processing. Each of these steps has an associated model, which can be used to replicate this process with any classified aerial photograph. Figure 13 shows the major steps taken in accomplishing this goal.

Figure 13: Steps for Identifying Missing Sidewalks



The first step of raster processing, after the segmentation and classification are complete, is to create the search area for sidewalks. If one were to process the entire image, then too many extraneous objects would be included as sidewalks. Since sidewalks generally occur along roadways, and all bus stops occur along roadways, then it makes sense to limit our search area for sidewalks to the areas along roadways. For the purposes of this research, the search area for sidewalks was determined to be between 40 feet and 16 feet of the roadway centerline. This was determined by using the measure tool in ArcMap to measure the distance from roadway centerline to the sidewalk on the area imagery. This step was repeated three times on the different road classes to determine an average distance. To then create the search area, two buffers were created from the roadway centerline, one for 16 feet and one for 40 feet. The 40-foot buffer is then erased by the 16-foot buffer, creating a polygon feature that excludes the roadway itself, but includes the area in which a sidewalk could be expected to exist.

This search area polygon feature is then applied to the classified aerial image. This is accomplished by using the Extract by Mask tool. The Extract by Mask tool allows for a portion of a raster, in this case the classified aerial image, to be extracted by a given mask, in this case the search area polygon. The result of this step is that the areas not within the search area have a “No Data” value, whereas raster values are retained within the area in which sidewalks could exist. This reduces the amount of processing that needs to be done to identify sidewalk segments. The raster now consists of only those parts of the raster that are within 16 to 40 feet of the roadway centerline.

Now that the raster was pared down to the search area, the “Calculate Statistics” tool was run. Running “Calculate Statistics” allows for further processing of the raster. Once the statistics were calculated, the raster could be cleaned up by applying generalization to the image. Generalization is a process by which small areas of the raster that have been misclassified are cleaned up. The tool used for generalization in this model was the “Majority Filter.” Majority Filter works by resampling the pixels around the misclassified areas to assign a new classification. The results were a smoother rater that eliminated some of the “messy” areas inherent in classifying an image. The variables of the majority filter were set to "EIGHT" and "MAJORITY".

These variables adjust the resampling method used in the classification, the “Eight” resamples eight nearest neighbors, and the “Majority” requires that a majority of these cells belong to a category before reclassification can occur. After this step, the classified raster was now clearer to see, and sidewalks were more uniform and pronounced.

Once generalization has been applied to the classified imagery, the next step is to extract the parts of classified image that could be sidewalks. Within the classification, each classification type is assigned a value. If there are seven categories in the classification, then each will have a unique value (1-7). Of these values, most sidewalks generally were classified as either sidewalk, or street. To extract these areas from the classified raster the “CON” tool was used. The CON tool uses an if/else statement on a raster’s attributes, which allows for parts of the raster to be extracted based upon their attributes. The “CON” tool has a Simple Query Language (SQL) block where the selection can be made. Before setting up the SQL code, the original raster should be checked to ensure the values assigned to the “sidewalk” or “street” classifications. For example, in one of the processes the raster’s value for sidewalks was “1” and the value for streets was “2”. The SQL code block is ["Value" <= 2]. Running the CON tool removes any part of the raster that was not either a sidewalk or a street, leaving only concrete surfaces. This completes the portion of the process that deals with raster processing. The next part will cover the processing of polygon features.

The next portion covers the model that completes the polygon process that identify sidewalks. At the end of the previous section, the result was a raster containing only the concrete surfaces, either sidewalk or street. This raster was converted into a polygon feature by using the “Raster to Polygon” tool. During this step, I ensured that the "Create Multipart Feature" option was checked so that the polygon features are separated as individual features and non-contiguous polygons were not considered one feature. The output of this feature was the same as the raster, but the concrete surfaces are now polygons. The importance of this step was that by converting the raster to polygons a number of polygon-only tools can be applied to the data for further processing.

Now that the data were all polygons, it was possible to remove the small features that were too small to be actual sidewalk segments. This was accomplished by using the select by attributes tool to select small features. In the SQL block of the tool, I used the formula ["Shape_Area <= 62], selecting all features with an area under 62. Once these small features are selected, they can be erased from the original polygon layer, leaving only the larger polygons. I then assessed an iteration of the “Multipart to Single Part” to ensure that all non-contiguous features would be assigned unique feature identifiers.

Since the small features that were not sidewalks had now been cleaned up, it was time to begin to tackle some of the larger features. Driveways proved to be one of the trickier features to remove from the picture. To process out the driveways, a negative buffer was used. A negative buffer is simply a buffer that uses a negative value. Instead of growing the object outwards, as is normally seen with a buffer, the negative buffer instead erased the feature inward. In effect this allowed driveways to be identified and then removed. Measurements of driveways were taken throughout the study area. The average driveway was found to be 6 feet wide. To remove the driveways and negative buffer with a value of -2.8 feet was applied. This negative buffer removes all sidewalks and leaves only a small sliver of polygon in the middle of the driveways. These slivers are then re-buffer out by 2.8 feet. This creates a polygon feature that has the extent of the driveways, without the sidewalk segments. The driveway layer was then erased from the original feature, leaving only the sidewalk segments. This step worked best in residential areas and worked less well in industrial areas. If this step is applied to an industrial area or a downtown area, it is best to omit this step.

Once the driveways had been removed, it was necessary to once again clean up the sidewalk layer. Due to the way that the polygons have been processed, many of the sidewalks have irregular shapes. To clean this up, I ran a negative buffer of -1.45. This will eliminate any features that are too skinny to be a sidewalk, while preserving the actual sidewalks. I then re-buffered by 1.45 to create a smoother polygon feature.

The now smoothed polygon feature was then processed again with the “Multipart to Single part” tool. Again, this was to break up any non-contiguous features. Next, I re-ran the selection of polygons with a shape area less than or equal to 62 and erased those features from the original polygon layer. I then repeated the process of selection and erasure, but modify the parameter to remove those shape lengths less than 45. Polygons that had a length of less than 45 were determined not to be sidewalks when compared to the aerial imagery.

Since Des Moines had planimetrics of many features, I elected to erase these from the polygon feature in order to further clean up the original layer. Planimetric were used to erase the model include parking lots, building footprints, and driveways. It was not necessary to use planimetrics, but since they were available, I felt it would be best to use them.

After examining the resulting layer, I identified that there were still some very large and very small features that were not sidewalks. Very large features are generally found in industrial areas, where the ground cannot be distinguished from roadway or sidewalks due things such as loading docks, warehouses and processing areas. Very small polygons are left over "slivers" from previous steps where features were erased from one another. For this selection, I used the parameters of [Shape_Area<=32 OR Shape_Area>=6936], which was determined through visual inspection of the previous outputs. I then erased this selection from previous polygon feature. The resultant layer is a polygon that contains features that best represent the location of sidewalks. This layer is used in the next step to create a line feature that identifies where sidewalks are missing.

The next model took the layer from the previous step and used it to create a line feature that represents where sidewalks are missing. The first step for this model was to clip the roadway centerline feature, which contained all roadway centerlines in the State of Iowa, down to the study area. This was accomplished by using the “Raster Domain” tool to create a polygon based upon the raster being processed. The street centerline feature was then clipped to the processing area.

Once the roadway centerlines had been clipped to the study area, the roadway centerlines could then be used to determine a “potential” sidewalk network. What is meant by “potential sidewalk network” is that every type of roadway that could theoretically support a sidewalk, i.e. not a limited access highway, has a sidewalk. This step allowed for the model to determine where sidewalks could exist, but are currently missing. To accomplish this the roadway centerline shapefile was used. The roadway centerline shapefile's attribute table contained a column, "StreetClas", which identified which type of roadway the line feature was. The categories were Interstate, Local, Minor Arterial, Private, Ramp, Alley, Arterial, Collector, and State Highway. The categories of Interstate, Ramp and Alley were not processed, as these roadway types would not be expected to have sidewalks. The remaining street categories were symbolized against the aerial imagery, and three measurements were taken for each Street Class of the distance from the centerline to the sidewalk. These measurements were then averaged to determine the average distance of the sidewalk from the street centerline for each street class.

Next a selection was made in the model for five street classes: Arterial, Minor Arterial, Collector, U.S. and State Highways (which grouped together), and Local. These classes were then buffered by the average distance of the sidewalk from the roadway centerline, creating a polygon feature whose outer edge represented the centerline of the potential sidewalk network. These polygons were then merged to create one polygon. Once merged, the "Polygon to Line" tool was applied to turn the polygon feature into a line feature. I then elected to erase this line feature by the planimetric of the roadways, which eliminated the lines that cross streets. I did this to simplify the model and reduce processing time. If no planimetric had existed, then the same process described above for determining sidewalk distance from the roadway centerline, could be used to determine the average distance from the roadway centerline to the edge of the roadway. At the end of this step, I was left with a line feature that represented the potential sidewalk network for the entire study area.

Now that the potential sidewalk network had been created, additional steps needed to be taken in order to allow the analysis to continue. Since this line feature had been created from a polygon, the entire potential sidewalk network formed one feature within its feature class. To identify which parts of it were missing, it was necessary to break it into many smaller features. Accomplish this, the "Split Line at Vertices" tool was used to make multiple line features. This ensures that shorter segments of sidewalk can be analyzed, instead of the entire section of sidewalk running along the whole street.

The next issue to overcome was the issue of (what I referred to as) “perpendicularity”. Since I wanted to use the “Near” function to identify which line sidewalk features did not intersect with the polygon sidewalk features found earlier, I had to determine a way to keep sidewalk line features from being within a search distance on the perpendicular. I only wanted those line features which were parallel to a polygon sidewalk feature, otherwise the “Near” function would identify that sidewalk as being within the search radius, when in reality the sidewalk was still missing. To overcome this issue, the model applied the “Feature Vertices to Points” tool, which turns every vertex into a point. Then I applied a buffer of 10.1 feet and erased this buffer from the potential sidewalk line feature. This removes the sidewalks from being within the 10 foot search area used in the next step. This process allowed me to solve the issue of perpendicular intersections. To compensate for the missing distance, a 20-foot allowance was added back into distance measures of the missing sidewalks later.

With the potential sidewalk network properly calibrated, the missing sidewalks could then be found. This step worked by comparing the potential sidewalk line feature against the polygon sidewalk feature that was determined from the classified imagery. It used the “Near” tool to search for extant sidewalks (the polygon feature) that are near the potential sidewalk (line feature) with a search radius of 10 feet. If the potential sidewalk fell outside of 10 feet from the final search area, then the “Near” tool writes a -1 into the “Near_Dis” column of the attribute table of the line feature. This identifies the potential sidewalks that are not near an existing sidewalk. The resultant layer shows all sidewalks that can be considered missing.

There were some issues with the model. The parameters of the model are designed to work best in residential neighborhoods, as these were the neighborhoods identified as being areas of need in the ESDA. The model performed worst in built up areas, such as downtown. This is due to the negative buffer to erase driveways. During this step, the large amounts of pavement downtown are identified as driveways by the model and erased. This could be corrected by removing that step from the model before running it downtown. Within industrial areas, there were similar issues as were encountered downtown. A similar solution could also be applied. Within neighborhoods, the largest issue was trees. Even though the imagery used was from the winter, the occluding branches and shadows caused by trees could often not be identified during the classification process, without also including other features. When a sidewalk was missing, but not detected by the model, it was due to another feature being identified as a sidewalk during the extraction process when it is something else. Loading docks, parking lots, and buildings very close to the roadway were the culprits of this oftentimes. A more detailed discussion of these issues can be found in the validation section.

4.4 Exploratory Spatial Data Analysis

Exploratory Spatial Data Analysis (ESDA) is a group of techniques, described by Anselin (1995) to identify patterns in spatial distributions of variables. Within this report, ESDA was used to identify areas of need within Des Moines that would benefit more from having sidewalks installed. Areas of Need are defined as block groups that meet the three criteria outlined above. They are block groups that have a low percentage of persons holding graduate degrees, a high percentage of Non-White persons and a high percentage of person below the near poverty level. This was accomplished by determining the global trend, whether there was clustering or not, and then drilling down to the block groups level to determine where clusters exist.

The first step of ESDA was to define the neighbor relationship of each block group. This definition was done using the program GeoDa to create two Spatial Weight Matrices. A Spatial Weight Matrix defines which geographies are near using different mathematical formulas depending on the type of method selected (Macedo & Haddad, 2016). As discussed in the variables section, I used three variables in this analysis: “Ratio of Income to Poverty,” "Percentage of Population with Graduate Degrees," and "Percentage of Population that is Non-White." These three variables were weighted, in turn, using the Queen's and k-nearest neighbor spatial weight matrices. Two different matrices were used to determine the robustness of the results. If both matrices produce similar results, then it showed that the results had a greater likelihood of being correct. A Queen weighting operates like how the queen piece operates on a chessboard. Block groups which border each other are assigned a value of 1, while block groups that do not share a border are assigned a 0. K-nearest neighbor weighting looks at neighbors based upon the manipulation of the variable *k*. For example, if *k* is assigned the value of 6, then the weighting matrix will assume that all block groups have 6 neighbors for weighting purposes (Macedo & Haddad, 2016).

Once the Spatial Weight Matrices were constructed, the next step was to determine if there is global spatial autocorrelation, which investigated if there was clustering between the geographic unit and the socio-economic variables. This was done by calculating the Global Moran's I statistic for both spatial weight matrices. The Moran's I statistic measures how similar or dissimilar one area is to another. A Moran's I score of -1 would mean that the data is completely heterogeneous, while a score of +1 would mean that it is perfectly clustered (Guillain, Le Gallo, & Boiteux-Orain, 2006). Looking at the Moran's I statistic of the study area, I was able to determine whether poverty is occurring in a clustering pattern.

Having the Moran's I statistic indicates if the spatial autocorrelation was true globally, that is, across the entire study area. To look at specific patterns within the block groups however, I used *Local Indicators of Spatial Association (LISA)*. LISA is defined as a statistic that "gives an indication of the extent of significant spatial clustering of similar values around that observation" and "the sum of LISAs for all observations is proportional to a global indicator of spatial association" (Anselin, 1995). LISA allows for the display of four types of observations, High-High, Low-Low, Low-High, and High-Low. High-High refers a block group of high values being surrounded by other high values, whereas Low-Low refers to a block group of low values being surrounded by other low values (Clusters), while High-Low refers to a block group of high value being surrounded by low values, and Low-High refers to the reverse (Outliers) (Guillain, Le Gallo, & Boiteux-Orain, 2006). For the purposes of this study, LISA will allow me to identify the block groups that are within High-High clusters of percentage of poverty and non-White and Low-Low areas of percentage of people holding Graduate Degrees or higher. Areas of Need are defined as block groups that meet the three criteria outlined above. They are block groups that have a low percentage of persons holding graduate degrees, a high percentage of Non-White persons and a high percentage of person below the near poverty level. Using these three characteristics, I can determine the neighborhoods of Des Moines that have the greatest number of areas of need.

Understanding where these areas of need occur helped to create a framework for understanding where sidewalk improvements for connectivity could be the most useful for DART to focus on.

4.5 Automation

Automation involves creating a process that can be repeated over and over with minimal human involvement. Computer programs are a common example of automation. Computers use many layers of different programs to conduct several tasks, from the most complicated to very simple functions, such as to move a cursor across the screen. Within ArcGIS, Python is the preferred programming language to work with because it is free and open source. Moreover, Python is supported within the user interface of GIS, consequently being able to access and use all of the built-in tools that are native to ArcGIS (Zandbergen, 2015). Automation in this project was used to identify the missing sidewalks that should be prioritized by DART.

The goal for the Automation section of this report was to create list of missing sidewalks ranked by priority for improvement, which would serve to enhance connectivity. This was accomplished by developing a Python script that calculated a need score for each missing sidewalk segment. The script generated a score for each missing sidewalk segment based upon its location within an area of need and its proximity to DART infrastructure. The inputs used in this script were the missing sidewalk features, generated in the Identifying Missing Sidewalks section, the LISA areas of need, generated in the ESDA section, as well as the bus stop and shelter locations, which were provided by DART. Since there were only three block groups that met all areas of need criteria, it was decided that the individual variables should influence the ranking, not just those sidewalks that were in an area of need. So instead of just giving one score to those sidewalks that fell within an area of need, each individual variable would be calculated separately. For example, if missing sidewalks occurred in a block group that met only one need variable (Low-Low Graduate), those missing sidewalks would receive a score of 10. If a missing sidewalk fell in an area of need (meeting all three variables) then it would receive a score of 30. Ranking the sidewalks in this manner allows DART to prioritize areas of missing sidewalk that would best serve its patrons.

The first step in writing the script was to set up the script to run in the current working directory, define variables that were to be used by the script and set up the relative paths so that the script could be used on other machines.

The next step was to spatial join the attributes used to determine the areas of need in the LISA to the missing sidewalk shapefile. A spatial join is a function which transferred a spatial attribute, such as the location of an object, into the attribute table of the object. The spatial join in this step transferred the attributes from block groups within areas of need (percentage Poverty and Non-White that were High-High, percentage Graduate Degree that were Low-Low) to the missing sidewalk features. These three different variables were selected, and then three separate spatial joins were conducted to transfer the LISA data to the attribute table of the missing sidewalk shapefile. These data were stored in a column of the attribute table labeled "LISA_CL". The missing sidewalks now have the variables for the areas of need stored within its attribute table.

Once the areas of need attributes were joined to the missing sidewalk layer, the next line in the script calculated a field code that replaced any Null values with 0. Arithmetic operation cannot be carried out on a Null value, so it was important to change Nulls to zeros to avoid errors in calculation. Once this was complete a new field (Rank) was added to the Missing Sidewalk attribute table to store the score of the areas of need. This field was added so that the values of the areas of need could be calculated into a score to be combined into a total rank for areas of need later.

The rank field was then calculated. If a missing sidewalk segment fell within an area with any of the need variables, it received a score of 10. At this point there were three different missing sidewalk layers, one for each of the need variables. Before proceeding these needed to be combined into one layer. This was accomplished by using two consecutive spatial joins, bringing the three layers together. A Feature Class to Feature Class was then executed to make the joins permanent. Running the spatial joins and the Feature Class to Feature Class avoided issues of data deletion that occurred whenever other methods for combining the data were used.

Next a field for "Total Rank" was added. This is the overall score for the three need variables to determine which missing sidewalks fall within the area of highest need. Each of the three rank columns then needs to be iterated through to convert any null values that may have been generated during the earlier steps into zeros. The total rank field was then calculated so that it summed the scores for each variable. Missing sidewalks that fell within areas of need had a score of 30, those that fell within a block groups that met two of the need variables received a score of 20, those that met only one 10, and if a missing sidewalk met none, then it received a score of 0.

Missing sidewalks ranked by the amount of need within an area could be of interest to the city of Des Moines, or neighborhood organizations within the city. To make the missing sidewalks more relevant to DART though, the distance the missing sidewalks occur from DART related infrastructure also need to be taken into account. For this script the distance from bus stops and bus shelters was also considered. A quarter mile is a commonly used distance for calculating a walkshed. The Des Moines Comprehensive Plan of 1940 also used the quarter mile distance as a planning factor in its analysis of transit routes within the city (Filippini, 2014). Since a quarter mile distance has been used extensively as a measure for walksheds, and has a pedigree in Des Moines, it is the measurement applied in this study.

To add a relevant distance score to the area of need score, quarter mile distance from the bus stops and shelters needed to be calculated. Bus Stops and shelters were each buffered by a quarter mile. This quarter mile buffer was then spatially joined to the missing sidewalks layer. Using the same steps as described in determining the areas of need to calculate the score, a ranking was created which gave a score of 10 to any missing sidewalk falling within a quarter mile of a bus stop, and an additional score of 10, if the missing sidewalk also fell within a quarter mile of a DART shelter. If a missing sidewalk segment fell within an area of need, and was within a quarter mile of a shelter, then it received a score of 50, the highest ranking.

This script was written to provide DART with a priority list of where improvements on missing sidewalks could be made. Results of this analysis will be discussed in section 5.2 Identifying Missing Sidewalks. Additionally, this script was written with the intention that it could be used by other agencies than DART and applied to different areas of central Iowa. The variables of this script can be easily swapped out, if for example the city of Des Moines wanted to conduct its own analysis on other areas of the city. A preliminary analysis for the whole city of Des Moines can be found in section 5.5 Automation.

4.6 Validation

Validation ensures that the results that were found in this study are reflective of the actual conditions as they exist in the real world. Since this study relied heavily on models to identify where sidewalks are missing, the results of those models needed to be checked to ensure that they are finding the missing sidewalks that they set out to find. This step serves as an important link between this research and the real world.

During this step, in order to save time and money on transportation, validation was conducted using the raster image, open-source imagery from Google Maps and GoogleStreetView. These open source websites have been used to map 100% of the sidewalks within Washington, D.C. (Makeability Lab, 2018), and based upon these previous efforts it was determined that this method would be sufficient for this study. Validation was undertaken to validate that the missing sidewalk layer did indeed represent missing sidewalks.

The review of the missing sidewalks took place in three steps. The first step was to display the missing sidewalk layer over the aerial imagery. I went through by neighborhood, beginning in the northwestern corner and working my way to the southeast corner. If a missing sidewalk was created by the model, but a sidewalk was shown to exist on the imagery, then the missing sidewalk was removed, and it was noted as an error. The first few iterations of this process led to refinement of the model. After reviewing the sidewalks against the aerial imagery, if there existed ambiguity, then I looked at Google Maps for further verification. If there was still any ambiguity after checking Google Maps, then Google Street View was used to further check the image. Sidewalks that had heavy overgrowth from grass and weeds were left in the missing sidewalk layer, since they could present the same obstacles to connectivity as missing sidewalks.

When there was any doubt as to the condition of the sidewalk, I left it in the missing sidewalk layer.

The validation of the missing sidewalks identified errors in the model and refined the list of missing sidewalks down to those sidewalks that were truly missing or in a very unserviceable condition. Further discussion of the validation, including pictures of errors observed and other issues of sidewalk obscuration are discussed in section 5.4.

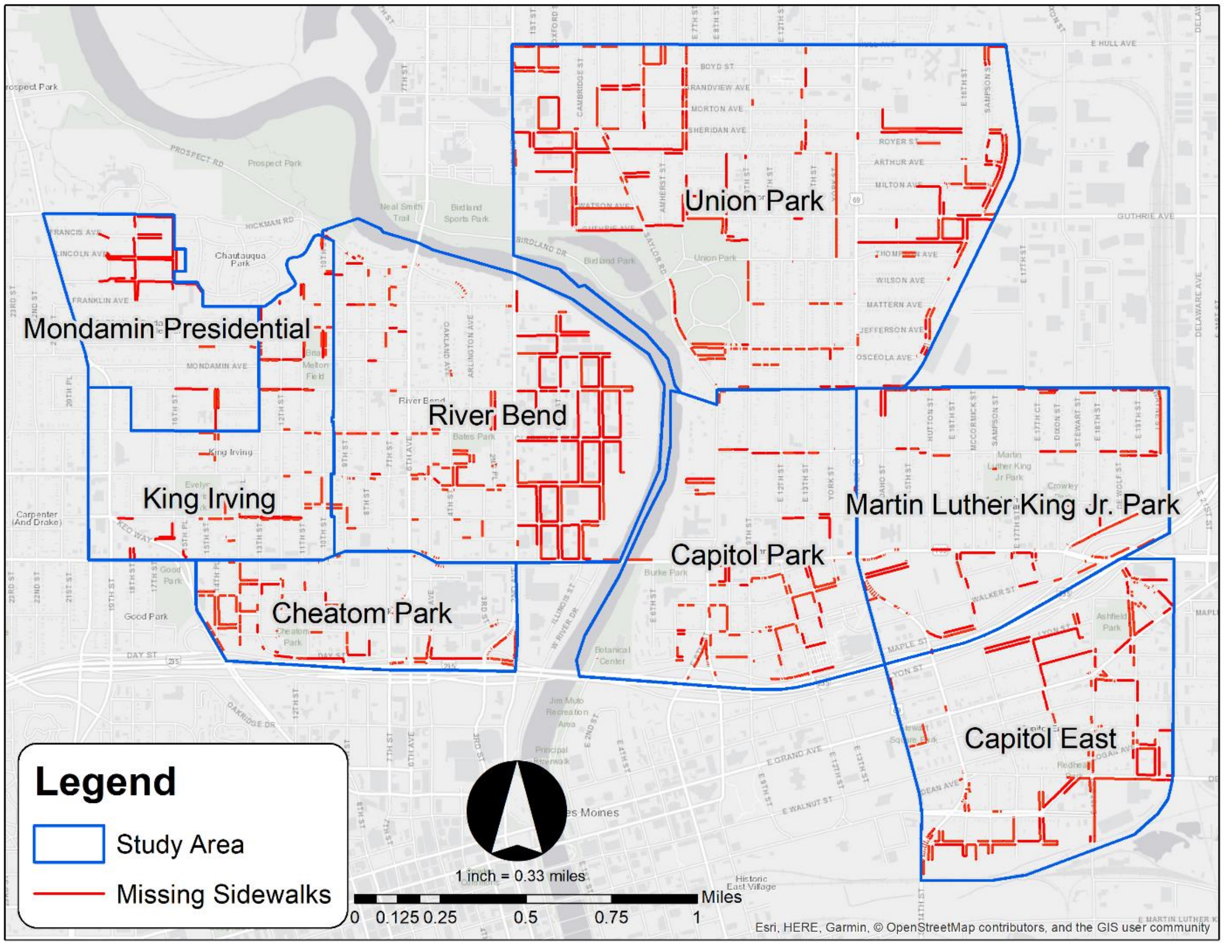
5. RESULTS

The results section of this report discusses the findings of the methodology described in the previous section. This section includes begins with a discussion of the descriptive statistics of the study area, describing it in terms of the three socio-economic variables discussed in the ESDA section. Then follows a discussion of the results of the models employed in the Identify Missing Sidewalks section. Next the results of the ESDA, including the global indicators of spatial autocorrelation and the local indicators of spatial autocorrelation are explained, followed by an identification of the areas of need and an overview of the neighborhoods in which they occur. Validation of the missing sidewalk layer is then examined, and issues and limitations of the models and methodology are laid out. Finally, the results of the Automation process are presented, followed by a detailed look at missing sidewalks within the study area and the priority missing sidewalks.

5.1 Identifying Missing Sidewalks

The result of the Spatial Analysis was a line feature representing the centerlines of all missing sidewalks within the study area. In total 928 missing sidewalks with a length greater than 30 feet (a constraint of the model) were identified within the study area. Visual inspection of the resultant layer showed that many of the missing sidewalks occur in industrial areas, such as in River Bend between 2nd Avenue and the Des Moines River. Other areas that stand out are the northwest and eastern sides of Union Park, the north of Mondamin-Presidential, the east side of Cheatom Park, and the south side of Capitol East (Figure 14).

Figure 14: Non-Validated Missing Sidewalks



These missing sidewalks were inspected in the Validation section, and a greater discussion as to the nature, type and count of missing sidewalks will be discussed there.

5.2 Exploratory Spatial Data Analysis

The results for the ESDA include the global indicators of spatial autocorrelation, which test the hypothesis of whether the percentages of Non-White, Poverty and those holding Graduate Degrees tend towards clustering within Des Moines, and the Local Indicators of Spatial Autocorrelation, which identifies geographic areas based upon their relationship to their neighbors. These results are used to identify the areas within Des Moines that have the greatest need. The areas of need and the neighborhoods that they fall into will be discussed in greater detail after the discussion of the ESDA results.

5.2.1 Global Indicators of Spatial Autocorrelation

The global Moran's I tests whether spatial autocorrelation among the three variables is occurring. This is illustrated in Table 8. Two different weight matrices were used to ensure greater robustness of the results. For each spatial weight matrix, the Moran's I value was calculated. A positive Moran's I means that similar values are located in similar locations, whereas a negative value for the Moran's would indicated the opposite. The pseudo P-value indicates the statistical significance of the observations. As shown in Table 8, all pseudo P-values calculated for these data has the smallest pseudo P-value possible at 0.001. This is below the 0.05 cutoff for significance, which represents a 5% chance that the observation is due to a random error. The z-value is calculated by dividing the mean by the standard deviation of the data and allows for the comparison of results between weight matrices and variables.

Table 8 lists these results by variables and the spatial weight matrix used. Statistically significant distribution was found for all the variables. This result is in line with the observations from the descriptive statistics of these variables. The Global Moran's I results were positive, allowing the rejection of the null hypothesis and indicating that there is clustering of these variables in Des Moines. Percentage of people with Graduate Degrees showed the strongest trend, followed by percentage Non-White, and finally percentage near Poverty.

From this information, we can assume that there is global spatial autocorrelation, meaning that there were areas that demonstrate a higher level of need. To determine local, the results of the LISA are discussed in the next section.

Table 8. Global Moran's I Results

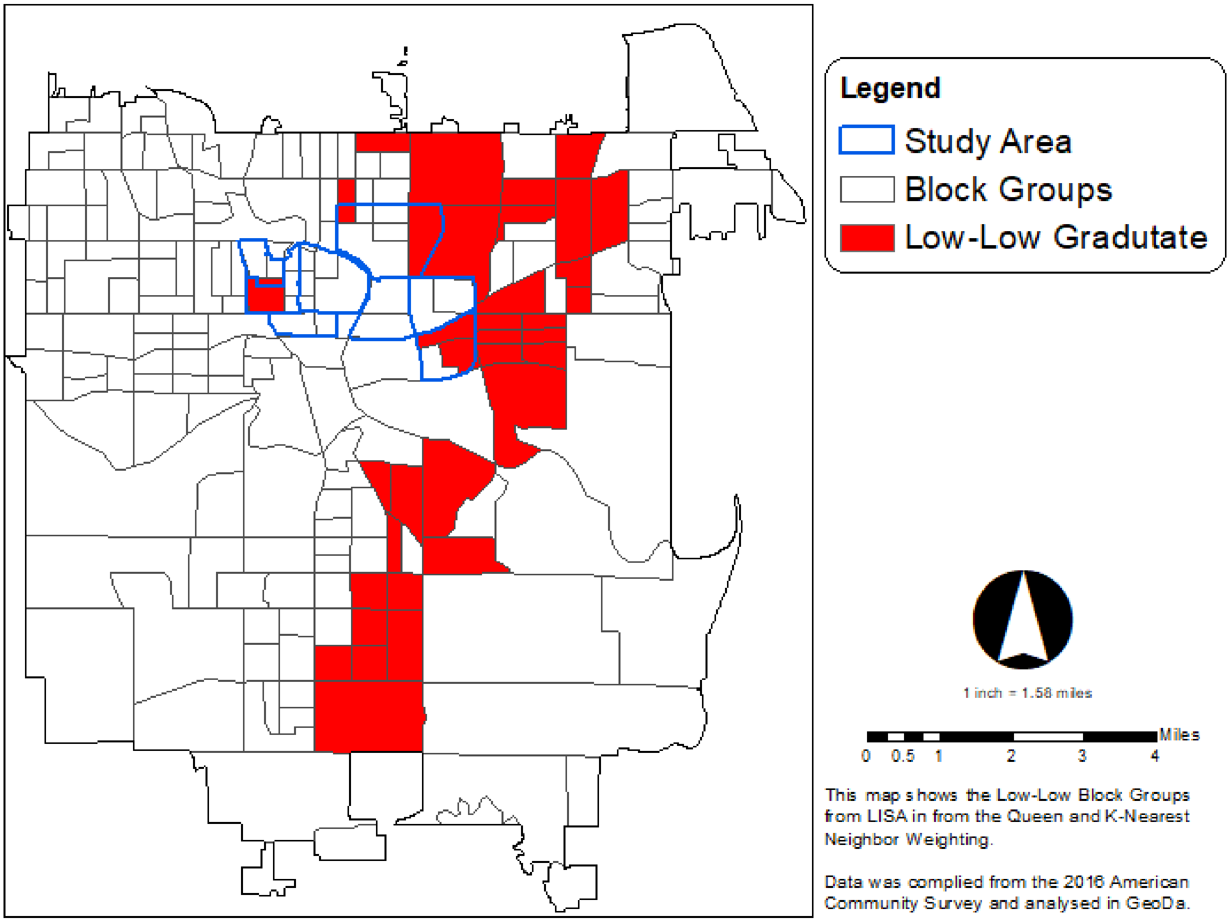
	Non-Grad		***Non-White***		***Near Poverty***	
	Queen	*K-Nearest*	*Queen*	*K-Nearest*	*Queen*	*K-Nearest*
Pseudo-P	0.001	0.001	0.001	0.001	0.001	0.001
Z Value	15.7	16.1037	13.27	13.68	8.41	9.209
Mean	-0.005	-0.006	-0.0056	-0.0054	-0.0041	-0.0061
Moran's I	0.629	0.619	0.53	0.522	0.343	0.37

5.2.2 Local Indicators of Spatial Autocorrelation

This section covers the Local Indicators of Spatial Autocorrelation or LISA. LISA is a measure of areas that have similar or opposite values. For this study, the block groups were used as the geographic level of analysis. The LISA analysis identifies clusters of block groups, which illustrates the relationship a given block groups has with its neighbors. The following maps illustrate those relationships by overlaying the results of both spatial weight matrices to identify the areas which were found to be in common between the LISA analyses, providing a more robust view of the data. Significance levels for observed block groups are for those with a p-value greater than 0.05, which means the chance of the cluster being random is less than 5%.

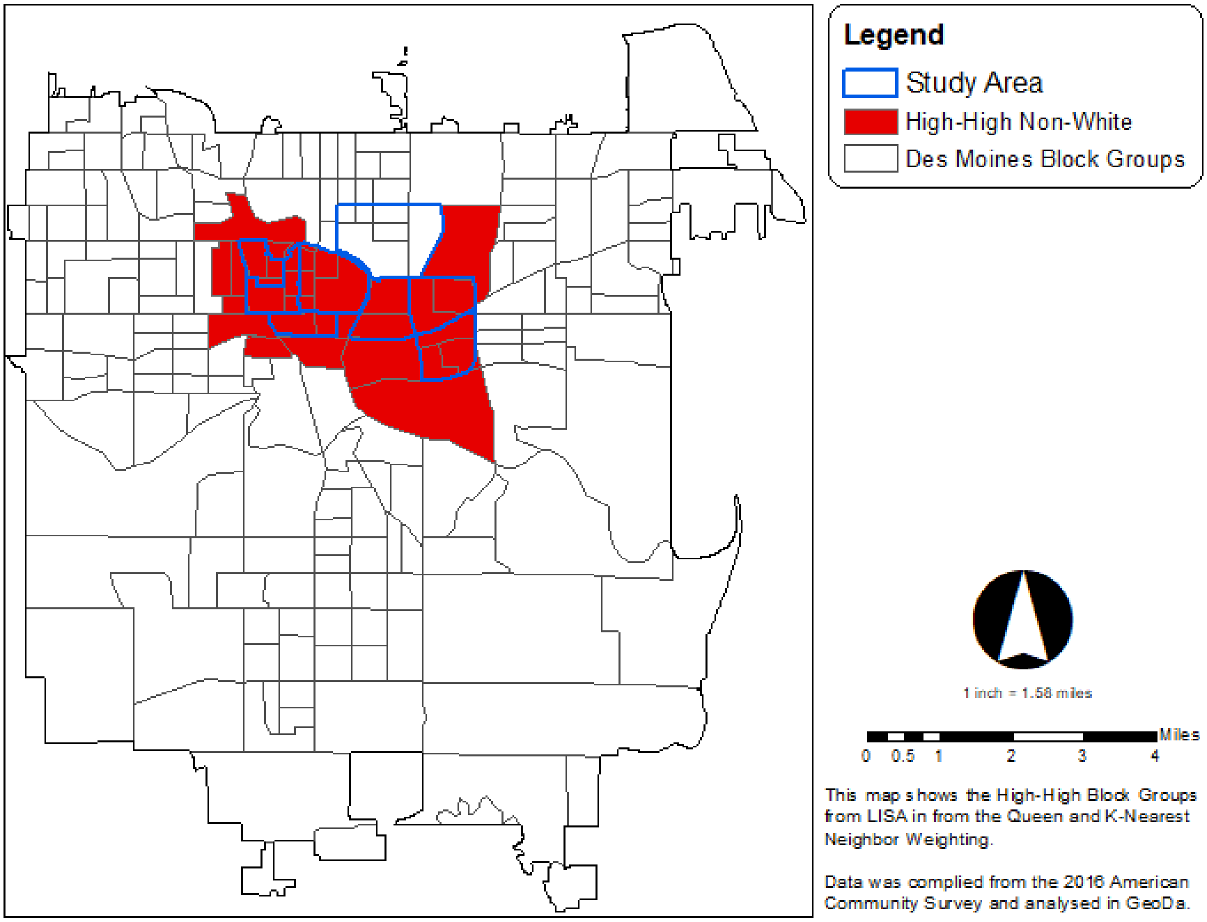
In looking at the LISA map of percentage persons with Graduate Degrees (Figure 15), a divide between the eastern and western sides of the city is evident. Anecdotal discussions that I have conducted with Des Moines natives often bring up the idea of an east side/west side divide in the city, with the western side being identified as upper class and the eastern side being identified as working class. East siders tend to wear this as a badge of honor. This anecdotal view of the city comes across in this map.

Figure 15: Percentage Graduate Degrees



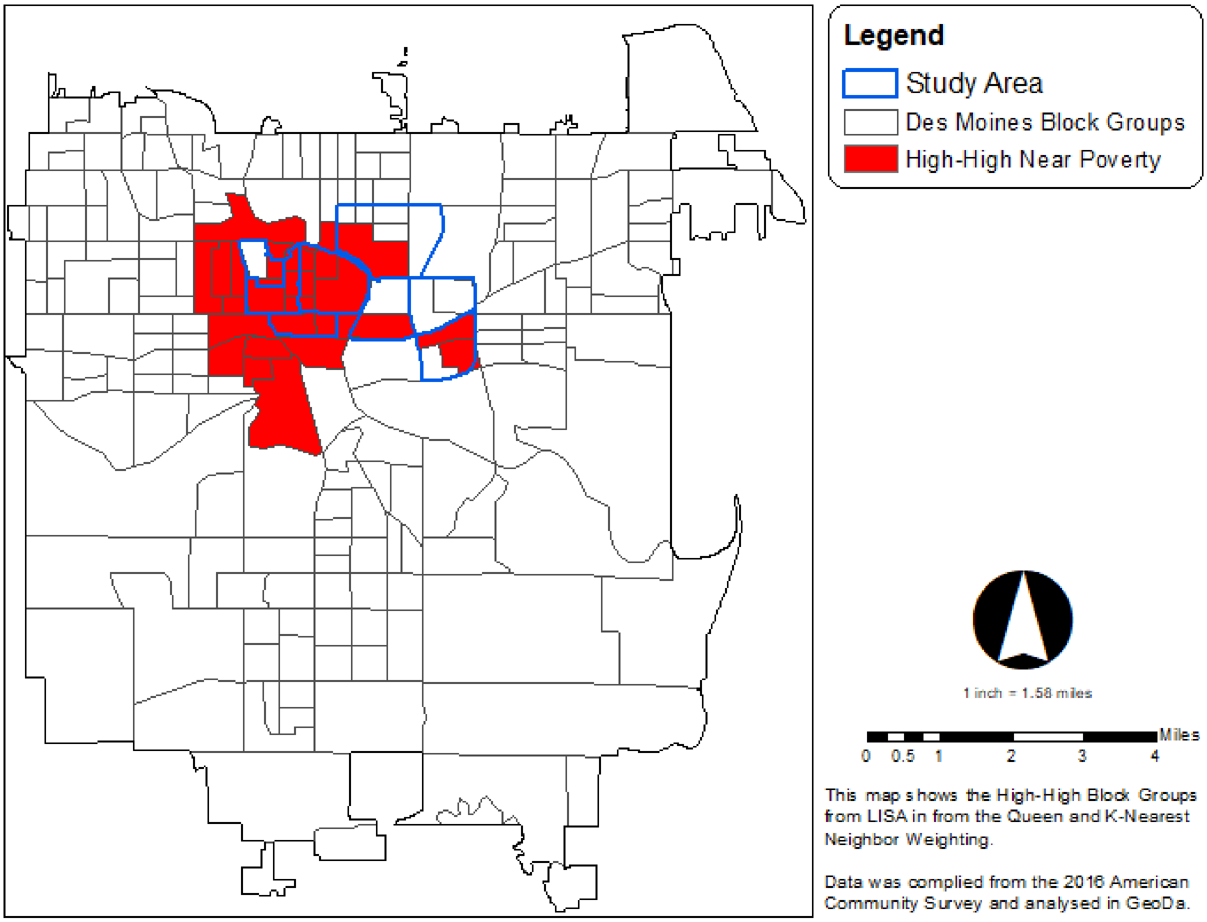
Viewing the LISA for the percentage Non-White (Figure 16), shows the highest block groups occurring north and northwest of the downtown. These areas correspond generally to the older neighborhoods of the city and demonstrate a pattern common in cities within the United States, where the downtown, and neighborhoods surrounding it, have a higher percentage of Non-White persons than the areas further away from the city center.

Figure 16: Percentage Non-White



The LISA map for the percentage of poverty (Figure 17), looks more similar to the map of Non-White, than it does to the Graduate Degree map. Many of the block groups to the northwest of downtown are not significant, which most likely represent areas which are Non-White, but do not have much poverty. Whereas one downtown block group, and two others on the western side are highlighted. These areas most likely represent block groups containing poor Whites.

Figure 17: Percentage Poverty



Having calculated the LISA for each variable by block groups, it is now possible to determine areas of need. Areas of need occur when there is a high percentage of poverty, a high percentage of Non-White, and a low percentage of those with graduate degrees. The block groups that were created by both spatial weight matrices were selected and then compared to each other to determine the block groups that had the highest level of need. This analysis identified three block groups, two in the Capitol East neighborhood, and one that makes up the majority of the King Irving neighborhood, with a small piece (3 blocks) in the Mondamin Presidential neighborhood.

5.2.3 Areas of Need

A closer look at the neighborhoods making up the areas of high need is warranted. The two neighborhoods in which both areas of need and missing sidewalks occur are Capitol East and King Irving. The below figures (18-20) show significant block groups throughout the study area. Three block groups, one mostly in King-Irving and two located in Capitol East make up the study area.

Figure 18: Low-Low Graduates with Missing Sidewalks

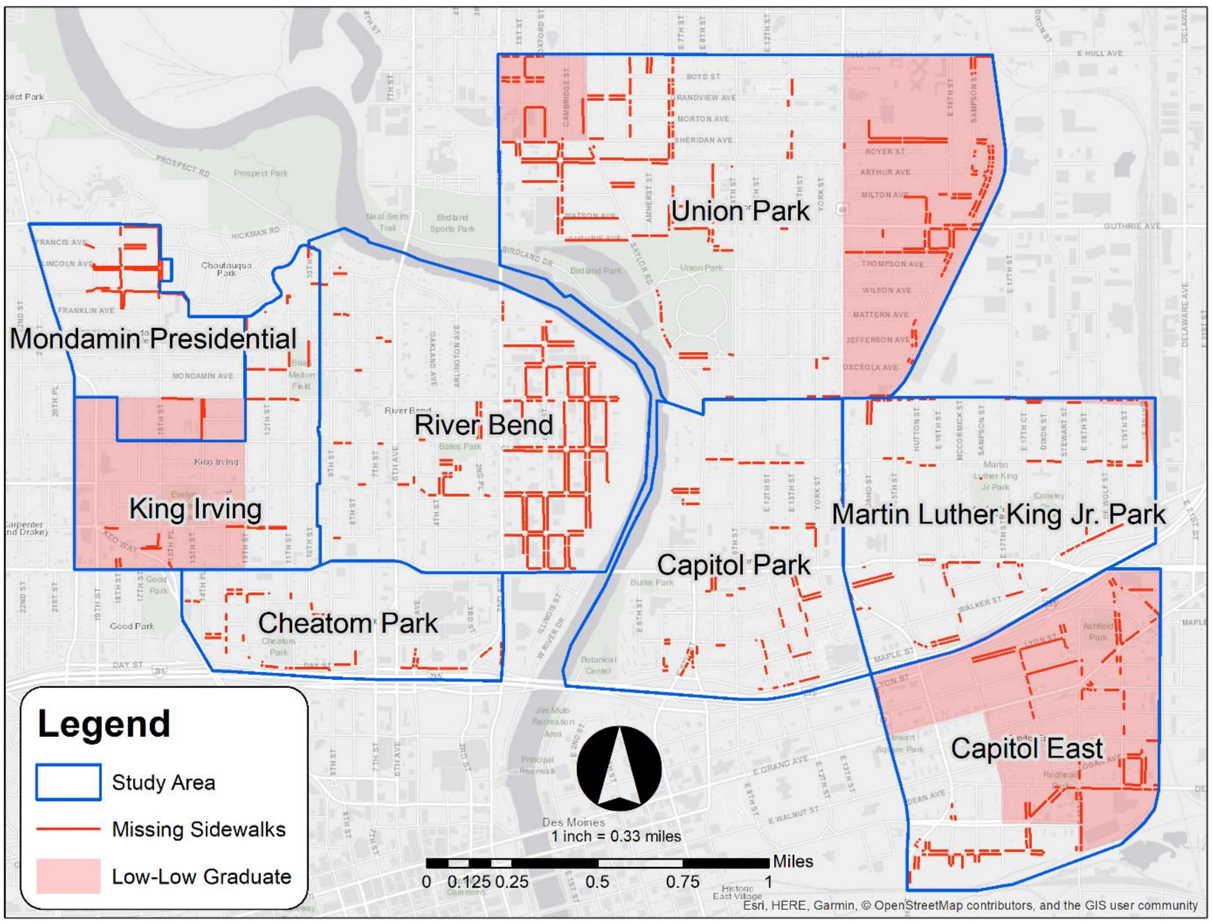


Figure 19: High-High Non-White with Missing Sidewalks

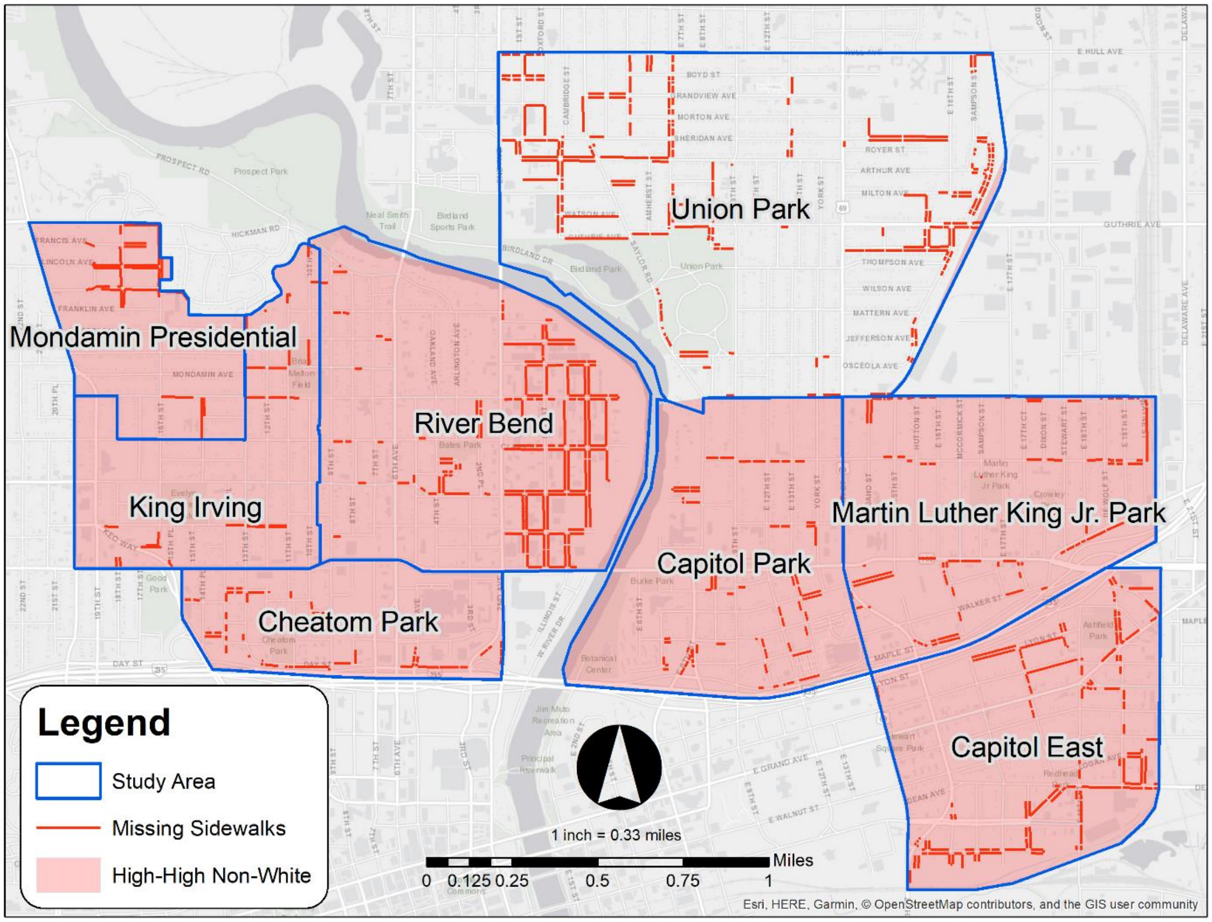
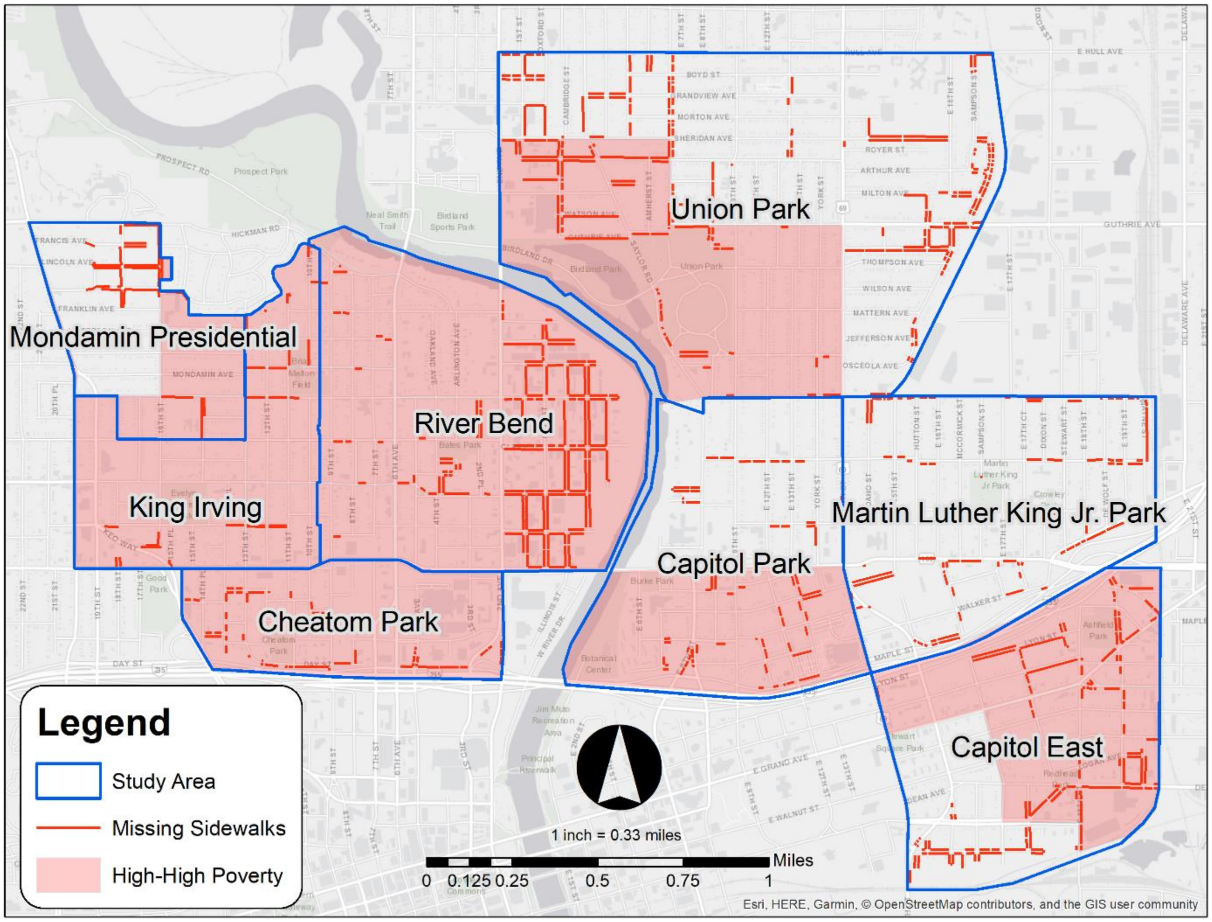


Figure 20: High-High Poverty with Missing Sidewalks



Capitol East is a diverse neighborhood lying due east of the State Capitol building. Capitol East is diverse neighborhood encompassing many people of different backgrounds. According to its neighborhood plan, dated 2014, the neighborhood was 14% African American and 32.5% Latino, 2% Asian and 60% White. The 2016 data, obtained from the American Community Survey, does not line up exactly with neighborhood boundaries, but seems to show an increase in the number of Non-White persons within the neighborhood. Since 2014, Non-White persons have increased from 48.5% to 59%. The number within poverty in the Capitol East plan of 2014 is not captured, however, the median income is reported in that document to be $20,803. Based upon the 125% of the poverty rate mark, outlined in the data section of this report, the percentage of persons below that mark in this neighborhood is 41%, a significant number. Persons holding a graduate degree are vanishingly small within this neighborhood. Only 0.01%, which is within the margin of error. It is safe to assume that very few people within the Capitol East neighborhood hold a graduate degree. Data from the 2014 neighborhood plan show that less than 0.05% of the population hold a bachelor's degree or higher.

Within the neighborhood plan from 2014, page 21 is concerned with sidewalk conditions. The plan points out many of the trouble areas identified by this study and include issues such as overgrown sidewalks and sidewalks in poor repair. Highlighting these areas again and providing a priority ranking to them is important for the improvement of the quality of life for the residents of the neighborhood.

The King Irving neighborhoods most recent plan comes from 2004 (King Irving Neighborhood Association, 2004). The neighborhood then was already significantly diverse, with most of the population being African American (51%), followed by Latino (15.3%), then Asian (12%). According to the ACS estimate from 2016, the neighborhood remains diverse, but with an increase in the Latino population (28.8%) and the Asian population (13%), and a decrease in the African American population (32.3%).

The neighborhood plan does not provide data on neighborhood income, but in 2001, the average home value was assessed at $34,404, $50,000 dollars less than the average value of a home in Des Moines. This indicates that the neighborhood was more low-income than the rest of the city. The current mean percentage near poverty within the neighborhood is 45.7%.

Within the neighborhood plan, goals of sidewalk improvements were mentioned twice. Residents of King Irving wanted a continuous sidewalk along Keosauqua Way, so that it would be easier for them to walk to Downtown. This goal was accomplished, as there is a continuous sidewalk along the western side of the road. The hill grade on the eastern side of the road near University Avenue make a sidewalk there unfeasible. Another goal was for general sidewalk improvements. The plan notes that 15,000 feet of sidewalk was repaired in 2002, and that 6,500 was repaired in 2003.

5.4 Validation

During validation, issues in the positive identification of missing sidewalks became apparent. Some of these issues were already discussed in the Spatial Analyst section, with regards to limitations within the model itself and how the model was calibrated for residential neighborhoods. Outside of any issues with the model, the majority of the false positives for missing sidewalks go back to limitations inherent in the initial segmentation and classification of the aerial imagery. The classification can only be as good as the raster image from which it is derived.

Trees were the greatest contributing factor to the model determining that sidewalk was missing, when it was not. Even though winter imagery was used, dense branch cover obscured the sidewalk. Including trees into the classification caused too many false positives however, so it was easier to identify and remove the falsely identified section.

Figure 21: Brick Sidewalk at 12th & Clinton

Non-concrete paving material caused the model to assume a sidewalk was missing when it was not. Due to the winter aerial imagery the brick sidewalks, seen here at 12th and Clinton in the Oak Park neighborhood (Figure 21), could not be separated from the dry grass during the segmentation. Brick sidewalks were noted in many of the older sections of the city, such as Oak Park, Capitol Park, and Capitol East. The sidewalk below (Figure 22), located at 18th and Grand in

Capitol East, shows some overgrowth as well. This sidewalk probably does not need to be replaced, just needs a good weeding.

Figure 22: Brick Sidewalk at E. 18th & Grand

Another issue was the angle of the aircraft when the aerial photo was taken. In Figure 23, you can see that from the aerial photo on the left, the sidewalk is obscured by the mass of the building, whereas, looking at the photo on the right, you can see that it clearly exists running along the edge of the building.

Figure 23: Sidewalk Hidden by Building

Leaf litter was another contributing factor in false identification. In areas where leaf litter is not cleared away from the sidewalk, there is no way that the classifier can determine the difference between the leaf litter and the surrounding grass. This sidewalk, near 13th & Arthur St in the Union Park neighborhood (Figure 24) illustrates the issue. The retaining wall, visible abutting the sidewalk, also reduced the amount of sidewalk present in the aerial photo causing the false positive.

Figure 24: Leaf Litter Covers Sidewalk E. 13th & Arthur

There were many places where the validation was correct. It was able to detect when sidewalks were completely missing in a residential area, as seen in this photo from E 19th St (Figure 25).

Figure 25: Missing Sidewalk (E. 19th St)

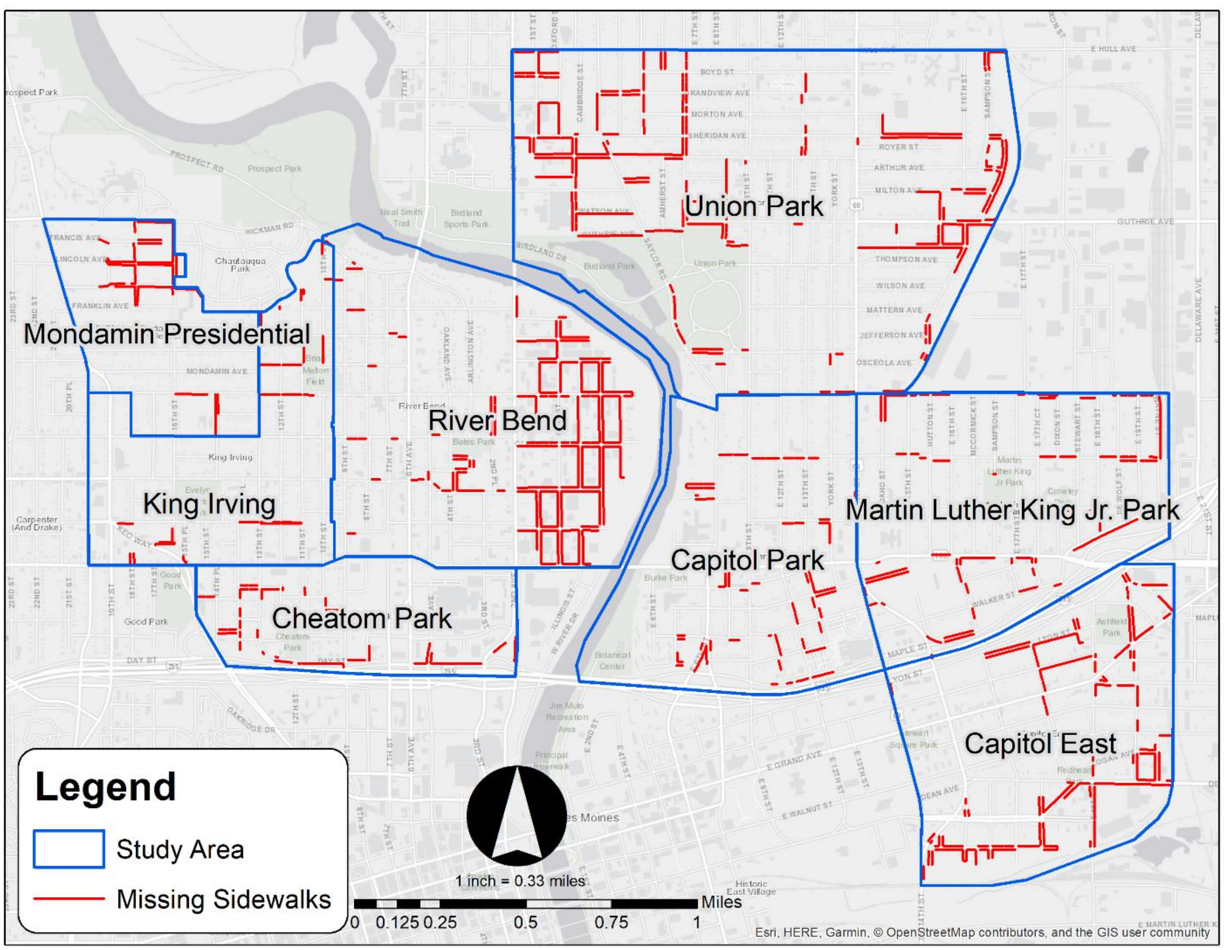
Additionally, the model returned a missing sidewalk when the sidewalk was badly damaged or overgrown with vegetation (Figure 26). This aspect of the model may be useful for those in the city's public works department who wish to identify sidewalks that are falling into a state of disrepair.

Figure 26: Sidewalk in Disrepair

After completing validation, 708 missing sidewalk segments were confirmed missing or badly damaged to the point that they were covered in vegetation or dirt, out of the 928 detected by the model. Detection of missing sidewalks by the model was correct in 76.3% of cases. This is slightly higher than the overall average geometrical completeness found by Kasemsuppakorn and Karimi in their study of identifying sidewalks from aerial imagery (68.91%) and similar to the 72.57% that they found in medium complexity environments (Kasemsuppakorn & Karimi, 2013).

The greatest impact of the model is in the time saved in detecting missing sidewalks. Running the model to detect missing sidewalks prevented me from having to review the entire study area manually and allowed me to focus my efforts on the areas most likely to be missing sidewalks. This method gives planners a tool that saves time when trying to identify missing sidewalks and provides a more structured way to go about obtaining this information.

Figure 27: Sidewalks Validated as Missing

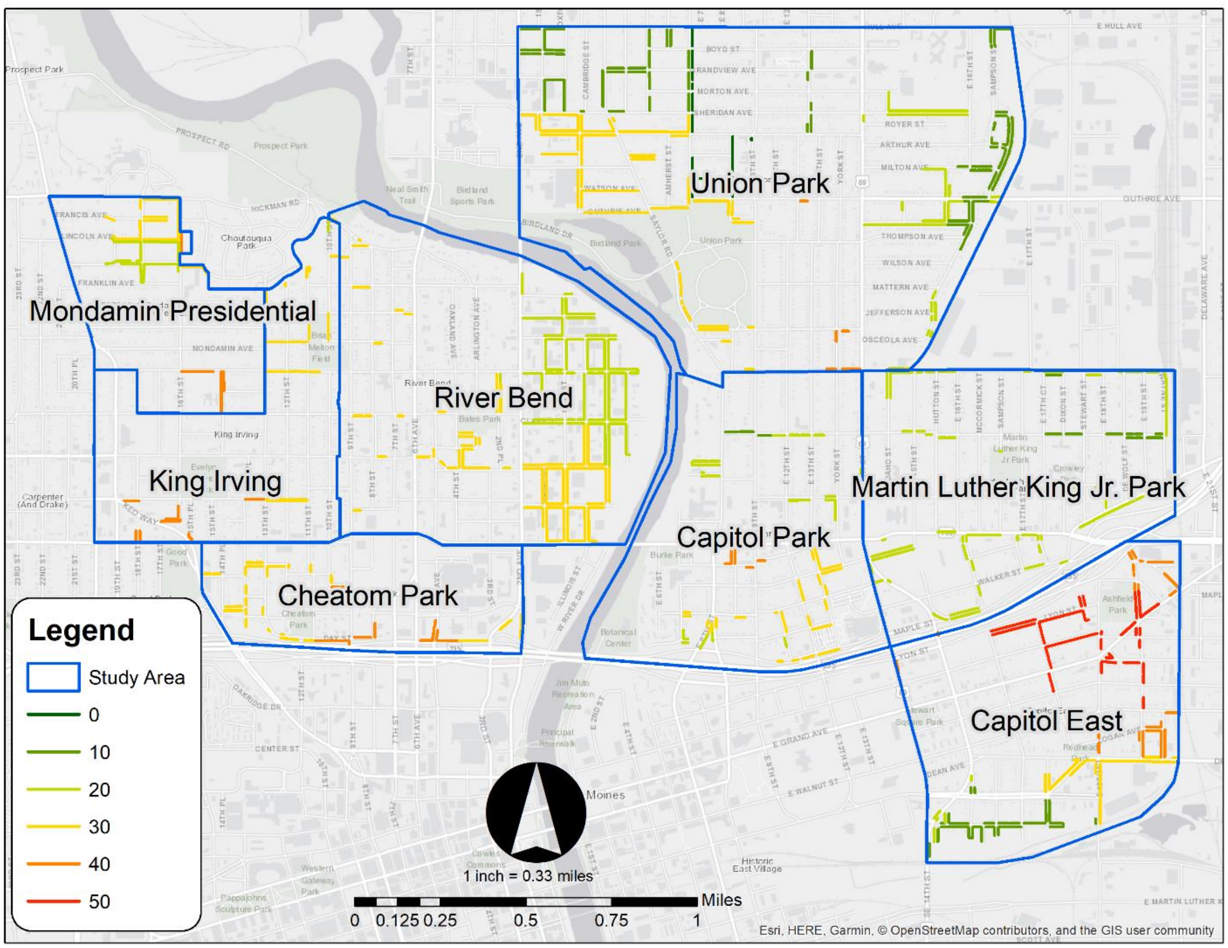


5.4 Automation

The final output of the automation process was a ranking of the missing sidewalks by areas of need and distance from bus stops and shelters. These data were compiled in a column in the missing sidewalks attribute table, which illustrated areas of need and distance to bus stops and shelters. This ranking goes from 0 to 50 in increments of 10. A score of 50 meant that a missing sidewalk is within an area of need and is within a quarter mile of a bus stop, and a quarter mile of a shelter. Lower scores represent areas that are further from bus service and have lower need. This priority ranking of sidewalks demonstrated where the greatest need for sidewalk connectivity occurred and will be useful in creating future plans for pedestrian improvements.

5.4.1 Study Area

Figure 28: Ranking of Missing Sidewalks



Of the 708 missing sidewalk segments validated, 39 segments were identified as meeting all the criteria to earn a total score of 50. This meant that within the study area, 5.3% of sidewalks were identified as being the highest priority. All of these highest ranked missing sidewalks occurred within the northeast part of the Capitol East Neighborhood. Within Capitol East 32% of sidewalks were identified as being the highest need.

Areas that had missing sidewalks with a score of 40 include the eastern side of Capitol East, on the border of the Fairgrounds neighborhood, central Capitol Park, a few areas in Union Park, areas around Mercy Hospital in Cheatom Park, and the central part of King Irving. Of these neighborhoods, only King-Irving contained a block group with the highest level of need. Although the neighborhood had this area of need, none of its missing sidewalks achieved the highest score, due to the lack of bus shelters within the neighborhood. This could point to a potential need for bus shelters to help promote equity. Potential location for these shelters could be located along bus route 16 in the vicinity of the Forest Avenue Library, or the corner of 13th Street and College Street, near the Grubb Community YMCA.

Other neighborhoods with missing sidewalks of a higher priority occurred in Union Park, Cheatom Park, and King Irving. Within Cheatom Park, missing sidewalks in the vicinity of 6th Avenue are identified as higher priority (Score of 40). Within Union Park, missing sidewalks are found on the eastern and western thirds of the neighborhood. Missing sidewalks in the vicinity of 2nd Avenue scored the highest within the neighborhood, due to an area of need, but are outside of the walkshed for bus stops.

Table 9 compares sidewalks between neighborhoods in the study area. The first column lists the existing sidewalk segments with the neighborhood. A segment is defined as the sidewalk that extends along one side of a block. For example, a square block would have four sidewalk segments. The next column shows the total length in feet of the existing sidewalks. Next, missing sidewalk segments are shown, followed by the estimated length of the missing sidewalk segments. The length is estimated, due to the sidewalks not existing currently. The next column shows the percentage of segments that are missing versus existing and the following column shows the same comparison, but between the length. The Length of Network column adds the length of extant sidewalks to the estimated length of the missing sidewalks to calculate the potential length of a fully built out sidewalk network. The final column then finds the percentage of missing sidewalks when compared to the length of the entire network, which indicates the amount of sidewalk missing within the neighborhood.

Table 9: Missing Sidewalk Statistics

Neighborhood	Existing Segments	Length (ft)	Missing Segments	Length (ft)	% Missing Segments	% Missing Length	Length of Network (ft)	% of network missing
Mondamin-Presidential	83	44,502	26	9,216	31.3	21	53,718	17.2
King-Irving	216	86,722	27	5,927	12.5	7	92,649	6.4
Cheatom Park	138	46,566	47	5,906	34.1	13	52,472	11.3
River Bend	294	115,664	132	32,109	44.9	28	147,773	21.7
Capitol Park	485	92,088	66	9,565	13.6	10	101,653	9.4
Union Park	405	176,951	215	39,360	53.1	22	216,311	18.2
Capitol East	451	82,444	115	20,467	25.5	25	102,911	19.9
MLK Jr. Park	405	93,502	80	13,065	19.8	14	106,567	12.3
Total	2,477	738,439	708	135,615	28.6	18	874,054	15.5

Looking at the neighborhoods as a whole, they differ in their distribution of sidewalks as well at the amount that is missing. Looking at existing sidewalks, the greatest number occurs in Capitol Park, with the least occurring in Mondamin-Presidential. The disparity occurs largely due to the difference in sizes between the neighborhoods. The neighborhood with the greatest area was Union Park with 805 acres, the smallest was Mondamin Presidential with 172 acres. Comparing the existing sidewalk segments to the area of the neighborhood explains the disparity in existing sidewalks between neighborhoods. The neighborhood with the densest sidewalks was King-Irving with 348.2 feet of sidewalk per acre, with the least dense neighborhood being Union Park, with a density of 219 feet of sidewalk per acre. More dense neighborhoods had more fine-grained pedestrian networks than less dense neighborhoods. The length of the existing sidewalks also followed a similar trend at the existing sidewalk segments. Differing neighborhood sizes and densities account for the differences seen between neighborhoods.

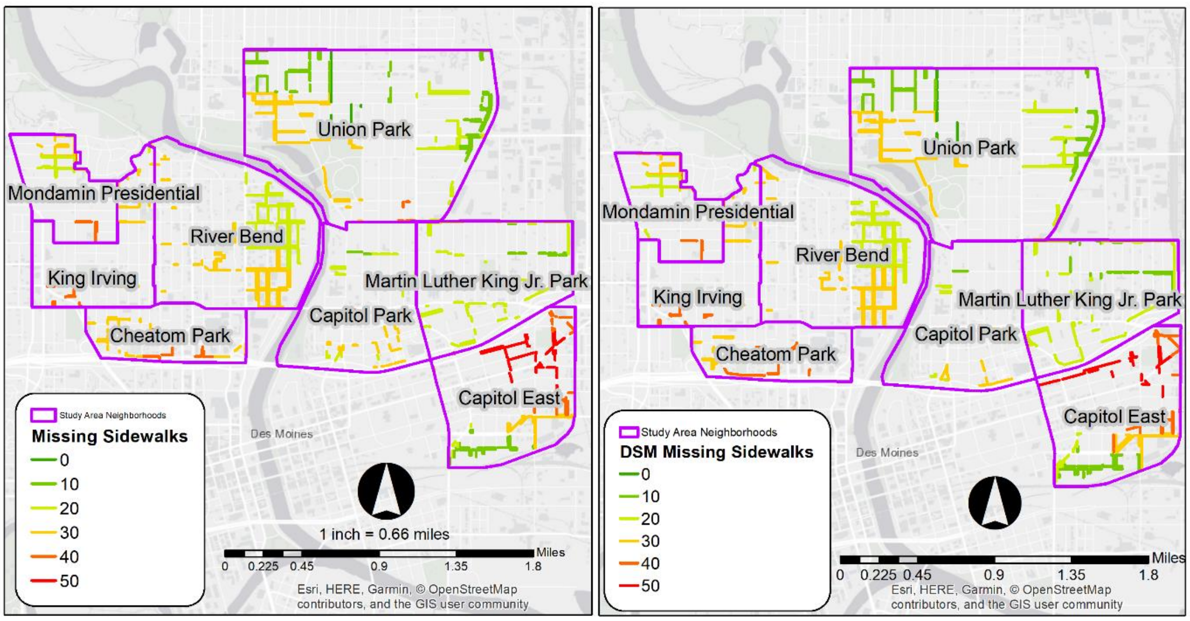
Missing sidewalk segments occurred in the greatest number in Union Park with 215, while the smallest number of missing sidewalks occurred in Mondamin-Presidential with 26 and King-Irving with 27. The small number of missing sidewalk segments can be attributed to investments made by Des Moines through the Neighborhood Improvement and Revitalization Program (NIPR) in 2002 and 2003. This program invested $1.56 million dollars into infrastructure improvements in the neighborhoods, including 21,500 feet of sidewalk. Additional sidewalk improvements were also made from 2004-2007 (City of Des Moines, 2010). Prioritized investments into this neighborhood made a huge impact even a decade later the amount of sidewalk in usable condition throughout the neighborhood.

When examining the final column, percentage of the network which is missing, the greatest percentage of missing sidewalks by length occurs within the River Bend neighborhood, with 21.73% of sidewalks missing from the potential sidewalk network. This is due to the industrial area located between 2nd Avenue and the Des Moines River having very few sidewalks. The next highest percentage was found in Capitol East, with 19.89%. This was particularly important as Capitol East was identified as an area of need. The third highest percentage of missing sidewalks occurred in Union Park, with 18.20%. Ranking fourth through seventh are Mondamin-Presidential, Martin Luther King Jr. Park, Cheatom Park, and Capitol Park at 17.16%, 12.26%, 11.26%, and 9.41% respectively. The neighborhood with the smallest amount of missing sidewalk based on length was King-Irving. As discussed in the previous paragraph, King-Irving was the recipient of focus on its pedestrian infrastructure based upon its 2004 neighborhood plan. The results of such a plan demonstrate the impact that planning can have on positively influencing the future direction of a neighborhood. The lessons learned from King-Irving can be applied to other neighborhoods.

5.4.2 Des Moines

One of the benefits of the script developed for this report, was that it did not rely upon the methodology to identify missing sidewalks to be useful. Any layer representing missing sidewalks could be analyzed with this script. This makes the script a more exportable tool for planners interested in missing sidewalks in their communities. As an example of this, the script was also run to a missing sidewalk layer obtained from the city of Des Moines, which contains missing sidewalks for the entire city. This layer was created manually through the visual inspection of aerial imagery. Processing this missing sidewalk layer for the study area with the script resulted in the image below (Figure 29).

Figure 29: Comparison of this reports findings (left), versus the City of Des Moines Missing Sidewalks (right)



The majority of the missing sidewalks outside of the study area were low in priority being ranked 20 or lower, indicating that they were outside of areas of need or not within a quarter mile of a bus stop or shelter. No sidewalks outside of the study area received the highest score of 50. Sidewalks meeting the criteria to have a score of 40 were found outside the study area, in the neighborhoods (from the North counterclockwise) Chautauqua Park, Prospect Park, Drake, Sherman Hill, and Fairgrounds. The main difference in the layers occurs along a Lyon St. in Capitol East. This area was not detected by the script, due to Lyon St being classified as an interstate highway ramp in the attribute table for street centerlines.

These results showed that the study area contains the greatest areas of need within Des Moines, but there are still neighborhoods outside of the study area that future studies could identify as benefiting from improved sidewalk connectivity.

5.5 Sidewalk Connectivity and Ridership

The objective of this study is to improve connectivity around DART bus stops. Improved connectivity will help DART to provide a better ridership experience for their patrons. The direct link between sidewalk connectivity and transit use has been explored in other papers (Cervero, 2001; Rodriguez, Aytur, Forsyth, Oakes, & Clifton, 2008; Woldeamanuel & Kent, 2015), with differing findings. Rodriguez et al. found that sidewalks were unrelated to people's walking to transit in two of the three cities that they researched. Cervero (2001) found that sidewalk connectivity was a factor in increased likelihood in commuters using rail transit and Woldeamanuel & Kent (2015) identified similar finding for sidewalk connectedness for a Bus Rapid Transit route. In the studies mentioned above, other factors, such as land use and socio-economic variables were found to be more important than sidewalk connectivity. An in-depth exploration of this topic was outside of the scope of this study, but a preliminary exploratory look at this question was undertaken.

To explore the connection between sidewalk connectivity and bus ridership, a shapefile containing all bus stops was joined to a table containing boarding data. Boarding data is automatically gathered when patrons board the bus. The electronic system for counting boarding is similar to systems used by stores to count foot traffic[7]. Of the 1,400 DART bus stops, the mean total boarding was 2,566. Below is a map of the study area, containing missing sidewalks and bus stops. The bus stops have been symbolized as being either above (green) or below (red) the mean ridership of 2,566. Higher levels of ridership occur on 13th St, 6th St, along Grand Ave and University Ave. Areas with higher ridership seem to correspond with land uses rather than with complete sidewalk networks. 6th Avenue has many shops and apartment buildings, and on its southern end, is located next to Mercy Hospital. Along University Avenue, there is the downtown campus of the Des Moines Area Community College.

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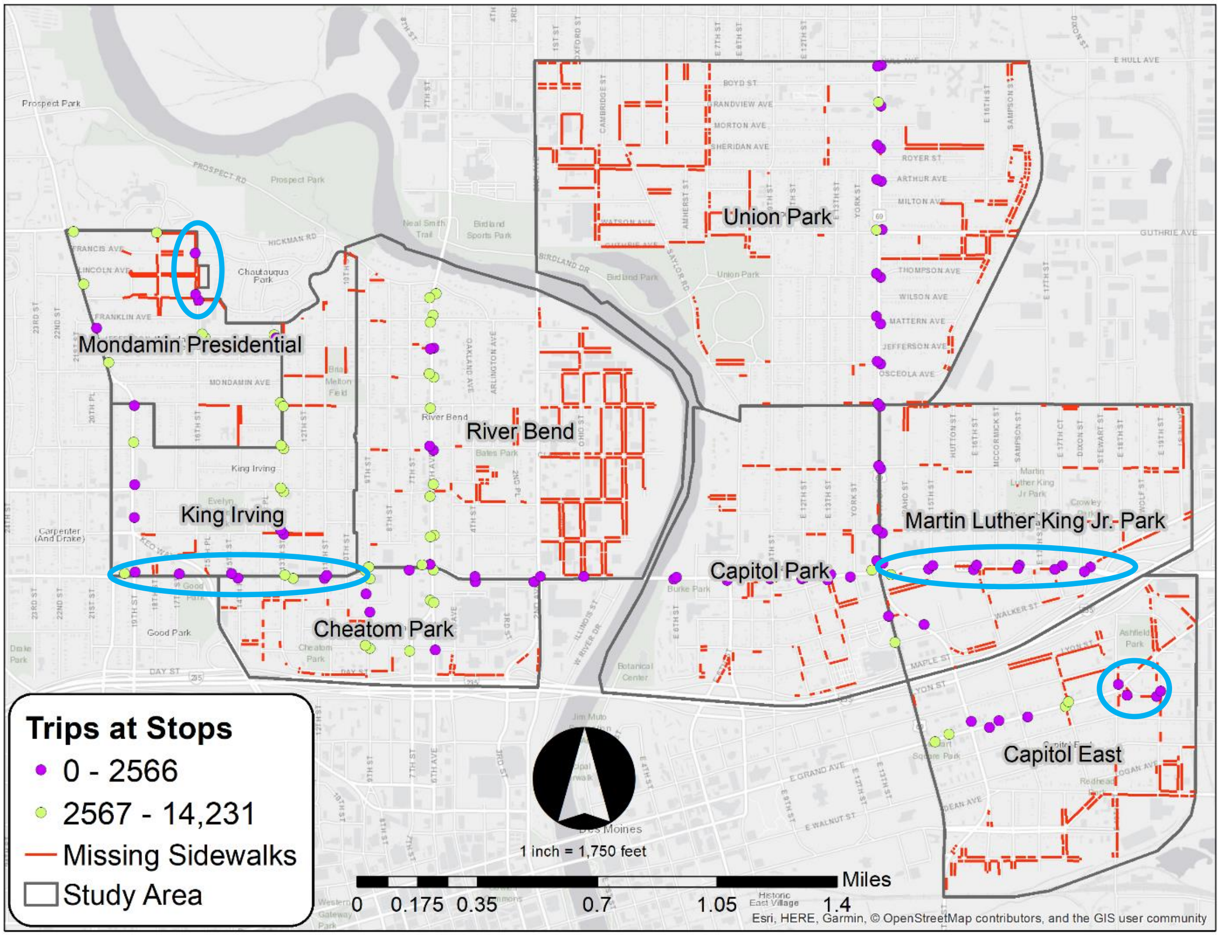
[7] In conversations with Carl, he expressed some reservations as to the accuracy of the count data, due to the electronic counters sometimes malfunctioning. For this reason, bus stops with a total boarding of zero were excluded from determining the mean.

Figure 30: Ridership and Missing Sidewalks



Missing sidewalks appear to have an effect on ridership in four places, identified by circles on Figure 30. Many of the areas that are missing sidewalks, such as in River Bend or the northwestern corner of Union Park are further away from bus routes. Route 4, which runs between Capitol Park and MLK Park into Union Park along E 14th Street has a majority of its bus stops below average ridership, but very few missing sidewalks along the route. Routes 3, 60 and 17 along University Avenue also have below average ridership on the majority of stops, and again have few missing sidewalks along the route. Bus stops with ridership below the mean did occur in some areas with missing sidewalks. In Martin Luther King, Jr. Park, at the corner of E. University and E. 17th Court, there is a bus stop near a section of missing sidewalk that had below average ridership at 2,271. On the east end of Capitol East, there are three bus stops located along missing sidewalks. Their average ridership was 2,244, 366, and 921.

This preliminary review of the link between sidewalk connectivity and bus ridership seemed to indicate that sidewalk connectivity was not a large factor in ridership. Other factors, such as level of service, land use and socio-economic characteristics around bus stops are more likely explanations for ridership level. Specific land uses, such as educational, medical and cultural, appeared more likely to influence ridership within Des Moines. In addition, socio-economic factors also likely play a large role in influencing the use of public transportation, due to the costs associated with private automobile ownership. Future studies within Des Moines could explore these factors and the links that these variables have to bus ridership.

6. CONCLUSION

This study identified a lack of sidewalk connectivity in areas of need around the bus stops of DART, specifically within the Capitol East neighborhood. This combined the analysis of aerial imagery to determine the location of missing sidewalks, the use of ESDA to find areas of need, and an automated script to rank the priority of missing sidewalks. For the first part of this study, identifying missing sidewalks, three models were developed which processed a classified aerial image into a line feature to represent the location of missing sidewalks. These missing sidewalks were then validated. Areas of need were then located through ESDA using three socio-economic variables at the block group level. A script was then written that ranked the missing sidewalks in importance for connectivity, by assigning a score based upon the missing sidewalks spatial location within an area of need and the missing sidewalks distance from bus stops. When all of these data came together, missing sidewalks were highlighted as being most needed within the Capitol East neighborhood of Des Moines. The results of this analysis are the basis for the following recommendations.

The first recommendation for DART is to use the information identified in this study and incorporate it into their updates to the DART 2035 plan. Missing sidewalks were already identified in previous plans as being important for improving the passenger experience, and this study provides for the first time, a vision for how to identify missing sidewalks and what priority those missing sidewalks should be. DART can then work with its partnership communities to apply Capital Improvement Project money towards sidewalk installation or apply for grants which would offset the cost of sidewalk installation in high priority areas. As demonstrated through the King-Irving neighborhood plan, long term plans for investing in pedestrian infrastructure make an impact on the built environment even a decade later.

Before beginning the process of sidewalk installation, conducting a survey or public meetings with a wide variety of community stakeholders would be recommended. There are limitations to conducting studies using data bases and software, and often that is the local knowledge that occurs within a community. Although the automation process may have identified certain missing sidewalks as being important, locals may know that a lack of sidewalk is forcing their kids to walk in the street to get to school. As such, the recommendations here should serve as a guide to focus priorities, and not as a final decision.

Specifically focusing on the results of this study, DART should focus initial efforts on missing sidewalks within the Capitol East Neighborhood. Capitol East had the greatest number of block groups with areas of need (2 out of 3 block groups). Capitol East has 12 bus stops and two shelters, and the entire neighborhood falls within a quarter mile of a bus stop, except for the far southern portion. Capitol East was the only neighborhood to have missing sidewalks ranked highest in priority. Focus on missing sidewalks along Grand Avenue and Hubbell would be the most visible impacts in this neighborhood, which serves as a link between the State Capitol and the State Fairgrounds.

After the Capitol East neighborhood, the King-Irving neighborhood would be another area to prioritize based upon need. It has 12 missing sidewalk segments, around Keosauqua Way and Carpenter Street that are around bus stops. These areas do not receive the highest ranking, due to a lack of shelters within the area, but should be another area of focus for DART in its efforts. Additionally, King-Irving has lessons that should be applied to other neighborhoods. As noted in the results, King-Irving has the second smallest number of missing sidewalk segments (27%) and the smallest amount of missing sidewalk network (6.4%). These numbers are not accidents. They are the result of deliberate action taken by the city of Des Moines based off of deficiencies noted in sidewalks in the neighborhood's 2004 plan. The results of this plan made a noticeable impact, even after more than a decade since it was first implemented. This is a testament to the power of planning and the impact that can be made upon the built environment. The plan, and implementation process for King-Irving should serve as a model for other neighborhoods that want improved sidewalk connectivity within their neighborhood.

The final recommendation is that DART should replicate the methodology described in this study across their entire service area, in order to identify area of need that could benefit from improvements in sidewalk connectivity. The methods outlined in this study were correct 76% of the time, which is a good start for analysis. This study showed that a planner using the tools available in ArcMap. The models for this study can save money and time with the speed at which they can be conducted, compared to digitization.

Moving forward, an analysis of the suburbs of Des Moines could point to areas of need outside of the city center. With a trend towards the suburbanization of poverty (Kneebone, 2010), it is important that planner expand the scope of identifying areas of need outside of the traditionally held idea of poverty in the inner city. This information would allow DART to show its importance in suburbs that may be more reluctant to contribute funding to DART and impact the conversation around public transportation in central Iowa. Replicating this study and refining it could not only assist DART in this process but could also be used by other planners in their practice.

When conducting the methodology outlined in this report, there were two main lessons learned to make the process easier and avoid issues. The first involved data management. To level data, i.e. the data gathered from other agencies and sources, should be kept in clearly-labeled folders. When processing data, using multiple, clearly-labeled geodatabases to store feature classes, allowed for easy access to the output of each process. The online help offered by ESRI provided clear understanding of how each tool was to run, as well as an example stand-alone or in-process Python script. The online help was consulted regularly throughout this study. Finally, the many pseudonymous contributors at the GIS Stack Exchange deserve much of the credit for the completion of the Python script. When problems arose in trying to figure out how to get a process to work in the script, it was often the most useful place to turn, and is full of people providing constructive help and tips. I recommend anyone working with Python in GIS sign up for the website.

Sidewalks serve as a connection for people and, as planners, people are ultimately for whom planning should be. This study has identified, in part of Des Moines, missing sidewalks that could hinder people from accessing the public transit that they require for employment, leisure, and education. This study demonstrated areas in which DART can focus its planning efforts and provided a methodology for expanding the identification of missing sidewalks to the entire DART service area. Importantly, this study has provided a replicable methodology for achieving that identification. This study has developed tools, three models and a Python script, compatible with ArcGIS that can be used by planners to prioritize missing sidewalks within their communities. These tools can be used by anyone knowledgeable in ArcGIS and basic Python to improve the lives of those in their communities.

This study is not just applicable to DART. The methodology described can be adapted to look at sidewalk connectivity, which could be of more interest to city governments. Other variables besides bus stops, such as public services, schools and grocery stores, could be added to the script to identify other priorities for missing sidewalk improvement. An additional analysis of the land use, using the zoning overlay for the city, could provide more insight as to where missing sidewalks are occurring and how that impacts ridership.

In the face of climate change and increasing social inequality, planners need to work to provide a more sustainable future for the people they plan for. This study represents a small way to move toward a more sustainable future. Public transportation provides a way for people, especially those who are most vulnerable in our society, to fully engage in public life. By identifying missing sidewalks, and incorporating that information into future plans, planners create a more pleasant environment for those who need to access public transit.

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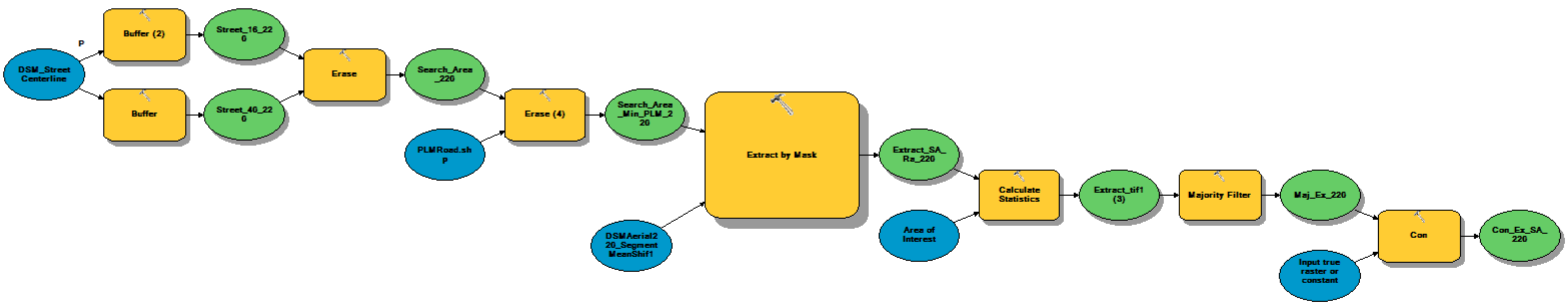
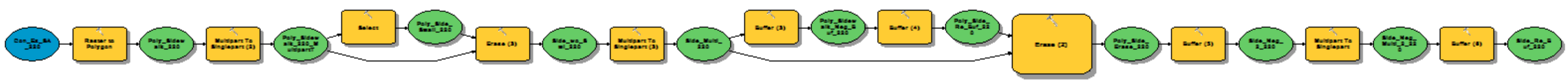
APPENDIX A: PYTHON SCRIPT FOR SIDEWALK RANKING

```
# Missing_Sidewalk_Ranking.py
# Created: May 2018 by Daniel C. Dvorjak, daniel.dvorjak@gmail.com
# Python Version 2.7.14
# Description: The purpose of this script is to create a priority ranking for bus stops.
# This is accomplished by comparing missing sidewalk segments to LISA Shapefiles representing areas of need,
# and distances from bus stops and shelters.


# Import arcpy module
import arcpy, os, time

time.clock()

# Check to see output geodatabase, create if none
cwd = os.getcwd()
baseCwd = os.path.dirname(cwd)
dataDir = os.path.join(baseCwd, 'Project_Shapefiles')
outputGDB = os.path.join(cwd, 'missing_sidewalk_rank.gdb')
if not arcpy.Exists(outputGDB):
    arcpy.CreateFileGDB_management(os.path.dirname(outputGDB), os.path.basename(outputGDB))

# Set up environment
arcpy.env.workspace = 'in_memory'
arcpy.env.overwriteOutput = True

# Variables
path = r'C:\Users\Daniel Dvorjak\Desktop\Project Shapefiles\Script'
LISA_POV = path + '\\LISA_POV.shp'
LISA_Non_White = path + '\\LISA_Non_White.shp'
LISA_GRAD = path + '\\LISA_GRAD.shp'
Bus_Stop = path + '\\BusStop.shp'
Shelters = path + '\\DARTShelters.shp'
Missing_Sidewalks_All = path+ '\\missing_sidewalk_rank.gdb\\Missing_Sidewalks_All_2'

# Start Processing
print(time.clock())

### The next series of steps identifies areas of need

##Process the LISA Non-White with missing sidewalks

# Select the block groups from the LISA Non-White that represent High-High clusters of Non-Whites
arcpy.Select_analysis(LISA_Non_White, outputGDB + "\\LISA_Non_White_Select1", "\"LISA_CL\" = 1")

# Spatial Join the High-High Non-White clusters to the missing sidewalks
LISA_Non_White_Select1 = outputGDB + "\\LISA_Non_White_Select1"
arcpy.SpatialJoin_analysis(Missing_Sidewalks_All, LISA_Non_White_Select1, outputGDB + '\\Missing_Sidewalks_NonWhite')

# Replace any null values in the Non-White shapefile with 0
Missing_Sidewalks_NonWhite = outputGDB + "\\Missing_Sidewalks_NonWhite"
arcpy.CalculateField_management(Missing_Sidewalks_NonWhite, "LISA_CL", "updateValue(!LISA_CL!)", "PYTHON_9.3", "def updateValue(value):\\n  if value == None:\

# Add Non-White Rank Field
arcpy.AddField_management(Missing_Sidewalks_NonWhite, "NonWhite_Rank", "LONG", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")

# Calculate Non-White Rank Field
arcpy.CalculateField_management(Missing_Sidewalks_NonWhite, "NonWhite_Rank", "[LISA_CL] *10", "VB", "")

## Process LISA Grad Degrees

# Select the block groups from the LISA GRAD that represent Low-Low clusters
arcpy.Select_analysis(LISA_GRAD, outputGDB + "\\LISA_GRAD_Select1", "\"LISA_CL\" = 2")

# Spatial Join the Low-Low GRAD clusters to the missing sidewalks
LISA_GRAD_Select1 = outputGDB + "\\LISA_GRAD_Select1"
arcpy.SpatialJoin_analysis(Missing_Sidewalks_All, LISA_GRAD_Select1, outputGDB + '\\Missing_Sidewalks_GRAD')

# Replace any null values in the GRAD shapefile with 0
Missing_Sidewalks_GRAD = outputGDB + "\\Missing_Sidewalks_GRAD"
arcpy.CalculateField_management(Missing_Sidewalks_GRAD, "LISA_CL", "updateValue(!LISA_CL!)", "PYTHON_9.3", "def updateValue(value):\\n  if value == None:\\n

# Add GRAD Rank Field
arcpy.AddField_management(Missing_Sidewalks_GRAD, "GRAD_Rank", "LONG", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")

# Calculate GRAD Rank Field
arcpy.CalculateField_management(Missing_Sidewalks_GRAD, "GRAD_Rank", "[LISA_CL] *5", "VB", "")

## Process LISA Poverty

# Select the block groups from the LISA Poverty that represent High-High clusters
arcpy.Select_analysis(LISA_POV, outputGDB + "\\LISA_POV_Select1", "\"LISA_CL\" = 1")

# Spatial Join the High-High POV clusters to the missing sidewalks
LISA_POV_Select1 = outputGDB + "\\LISA_POV_Select1"
arcpy.SpatialJoin_analysis(Missing_Sidewalks_All, LISA_POV_Select1, outputGDB + '\\Missing_Sidewalks_POV')

# Replace any null values in the Poverty shapefile with 0
Missing_Sidewalks_POV = outputGDB + "\\Missing_Sidewalks_POV"
arcpy.CalculateField_management(Missing_Sidewalks_NonWhite, "LISA_CL", "updateValue(!LISA_CL!)", "PYTHON_9.3", "def updateValue(value):\\n  if value == None:\

# Add Poverty Rank Field
arcpy.AddField_management(Missing_Sidewalks_POV, "POV_Rank", "LONG", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")

# Calculate Poverty Rank Field
arcpy.CalculateField_management(Missing_Sidewalks_POV, "POV_Rank", "[LISA_CL] *10", "VB", "")

##Join together all three data sets and create a new feature class

# First Spatial Join the Grad and Non-White Missing Sidewalk layers
arcpy.SpatialJoin_analysis(Missing_Sidewalks_NonWhite, Missing_Sidewalks_GRAD, outputGDB + '\\Missing_Sidewalks_Grad_NW')

# Then Spatial Join the Grad/Non-White to the Poverty
Missing_Sidewalks_Grad_NW = outputGDB + '\\Missing_Sidewalks_Grad_NW'
arcpy.SpatialJoin_analysis(Missing_Sidewalks_Grad_NW, Missing_Sidewalks_POV, outputGDB + '\\MS_Combine')

##Process Bus Stops and Shelters

#Buffer bus stop and shelters to a quarter mile (walkshed)
arcpy.arcpy.Buffer_analysis(Bus_Stop, outputGDB + '\\BusStop_Buffer', '0.25 Miles', "Full", "Round")
arcpy.arcpy.Buffer_analysis(Shelters, outputGDB + '\\Shelters_Buffer', '0.25 Miles', "Full", "Round")

#Spatially Join Bus Stops and Shelters to the buffers, to determine which sidewalks are within the walkshed
BusStop_Buffer = outputGDB + '\\BusStop_Buffer'
Shelter_Buffer = outputGDB + '\\Shelters_Buffer'
arcpy.SpatialJoin_analysis(Missing_Sidewalks_All, BusStop_Buffer, outputGDB + '\\MS_BusStop')
arcpy.SpatialJoin_analysis(Missing_Sidewalks_All, Shelter_Buffer, outputGDB + '\\MS_Shelter')

#Add Rank Fields
MS_BusStop = outputGDB + '\\MS_BusStop'
MS_Shelter = outputGDB + '\\MS_Shelter'
arcpy.AddField_management(MS_BusStop, "Stop_Rank", "LONG", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")
arcpy.AddField_management(MS_Shelter, "Shelt_Rank", "LONG", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")
```

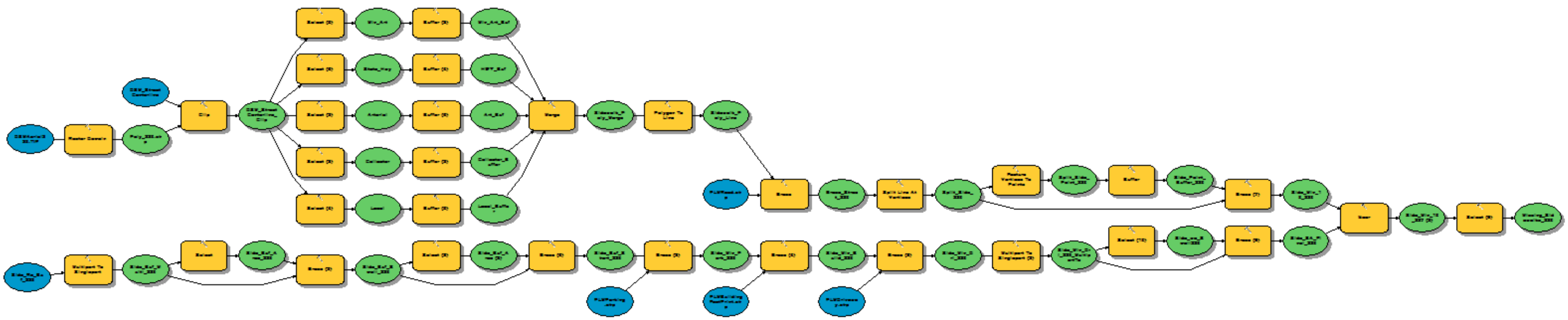
APPENDIX B: MODELS FOR EXTRACTING PAVED AREA FROM RASTER IMAGE



APPENDIX C: MODEL FOR CREATING POLYGON SEARCH AREA FOR SIDEWALK IDENTIFICATION



APPENDIX D: MODEL FOR IDENTIFYING MISSING SIDEWALKS



APPENDIX E: SOCIO-ECOMONIC STATISTICS FOR THE STUDY AREA, 2016

GeoID	Population	% Non-White	% Near Poverty	% Grad Degrees
191530052003	1,278	56	40	1
191530012002	838	78	41	5
191530049002	987	55	60	1
191530050002	1,379	90	46	2
191530005003	1,034	20	14	3
191530003002	2,333	29	11	7
191530048002	1,829	71	40	0
191530050003	840	64	43	1
191530015001	1,041	35	21	4
191530017001	1,429	84	29	2
191530012001	1,464	92	54	1
191530005004	970	22	43	7
191530017002	1,378	86	42	2
191530050001	566	49	41	0
191530012003	1,478	85	54	7
191530015002	1,926	37	24	4
191530049001	1,276	53	31	5
191530050004	928	78	58	0
191530005002	779	43	34	4
191530052001	1,046	68	49	3
191530052002	946	56	35	0
191530048001	1,575	79	39	3

APPENDIX F: MAP OF DES MOINES NEIGHBORHOODS